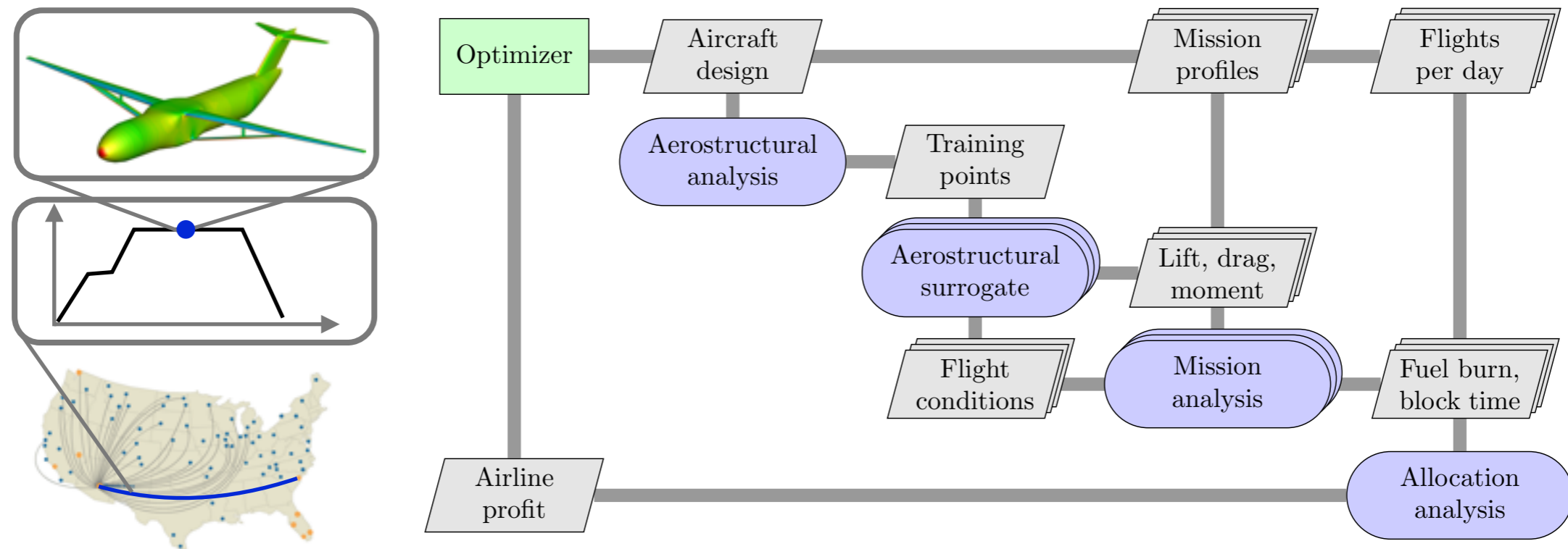


# Scalable multifidelity design optimization: Next-generation aircraft and their impact on the air transportation system



Joaquim R. R. A. Martins (PI)  
University of Michigan



Jason E. Hicken (co-I)  
Rensselaer Polytechnic Institute

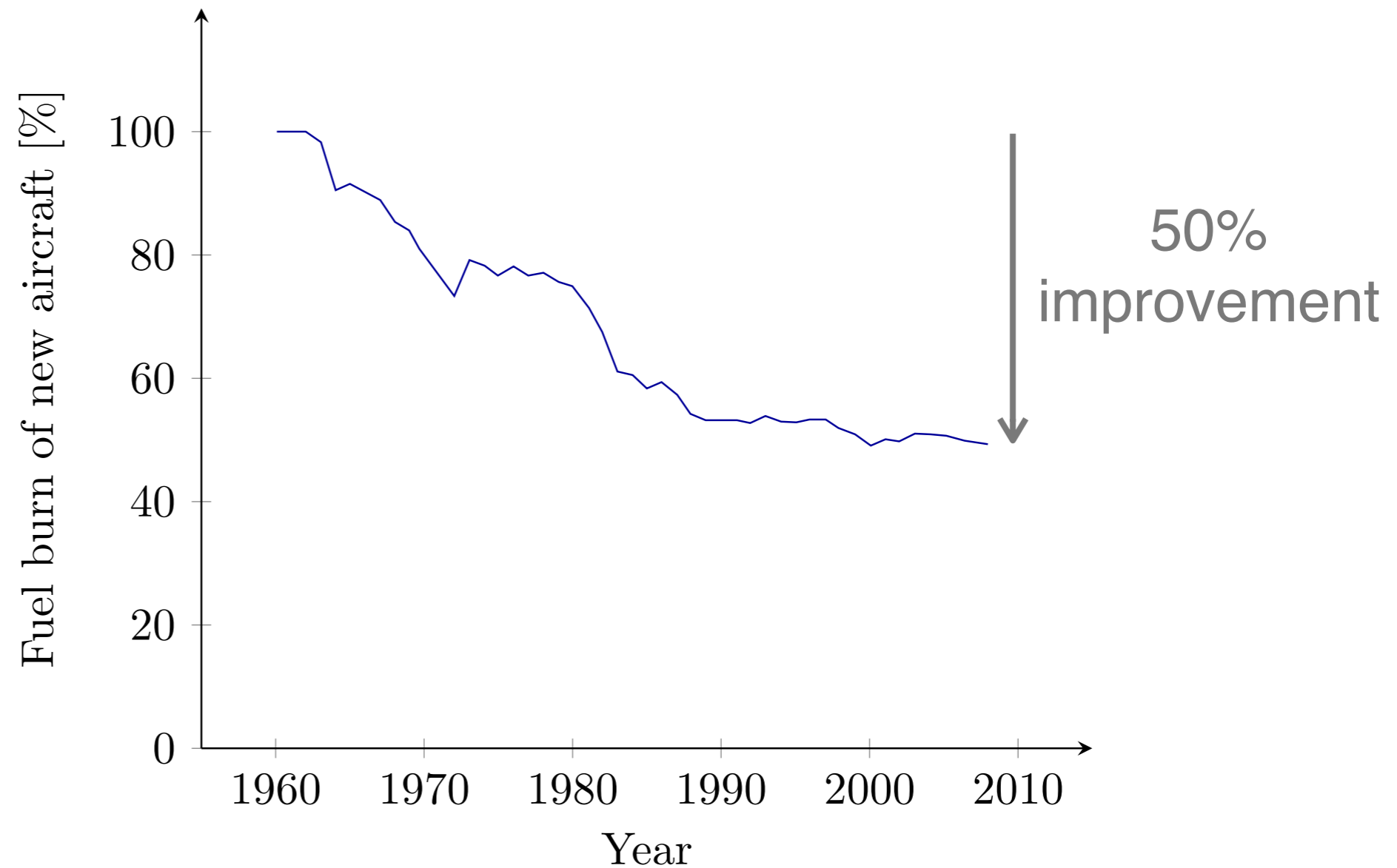


William A. Crossley (co-I)  
Purdue University



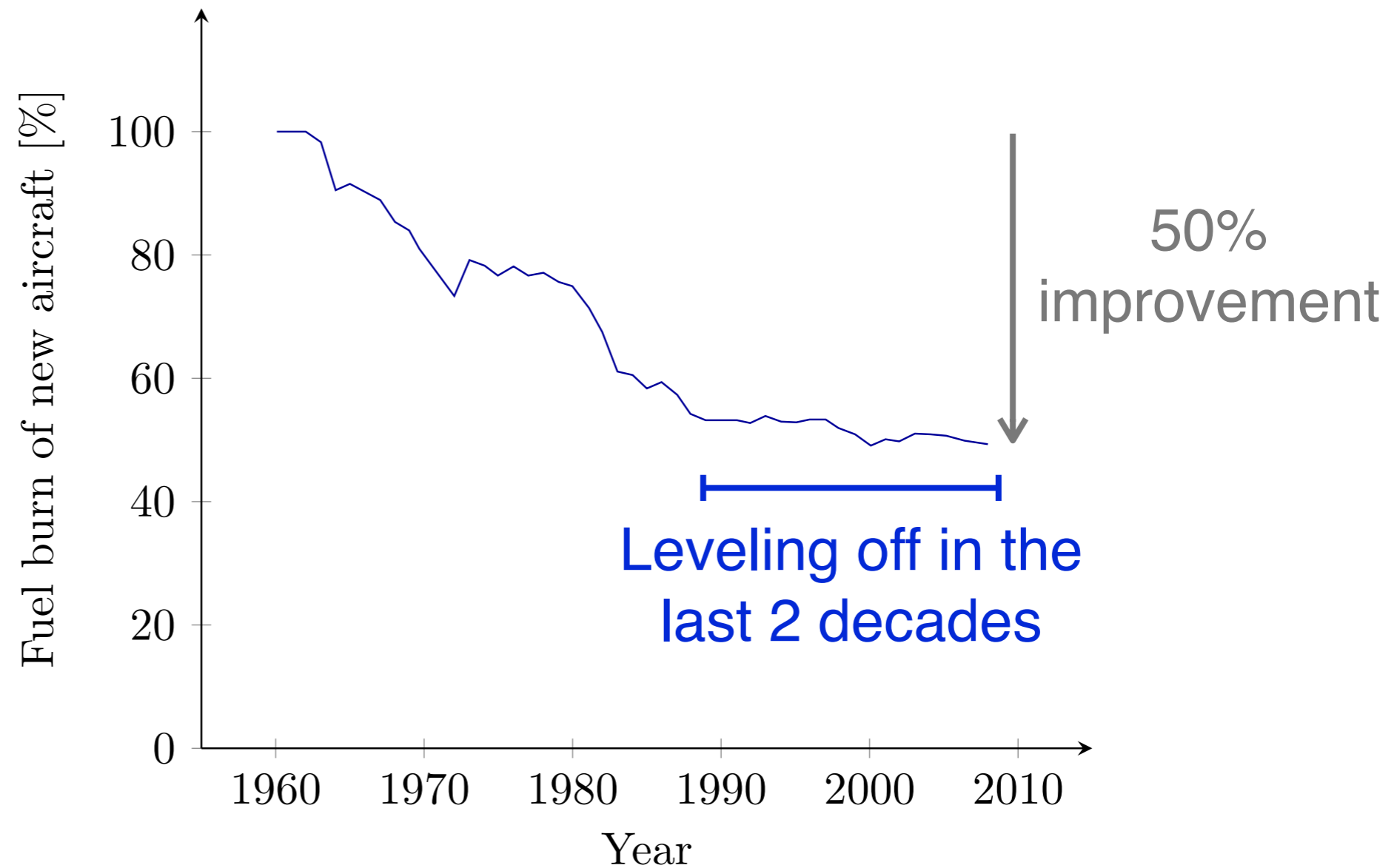
Karen E. Willcox (co-I)  
Massachusetts Institute of Technology

# Commercial aircraft designs have begun to plateau in fuel efficiency



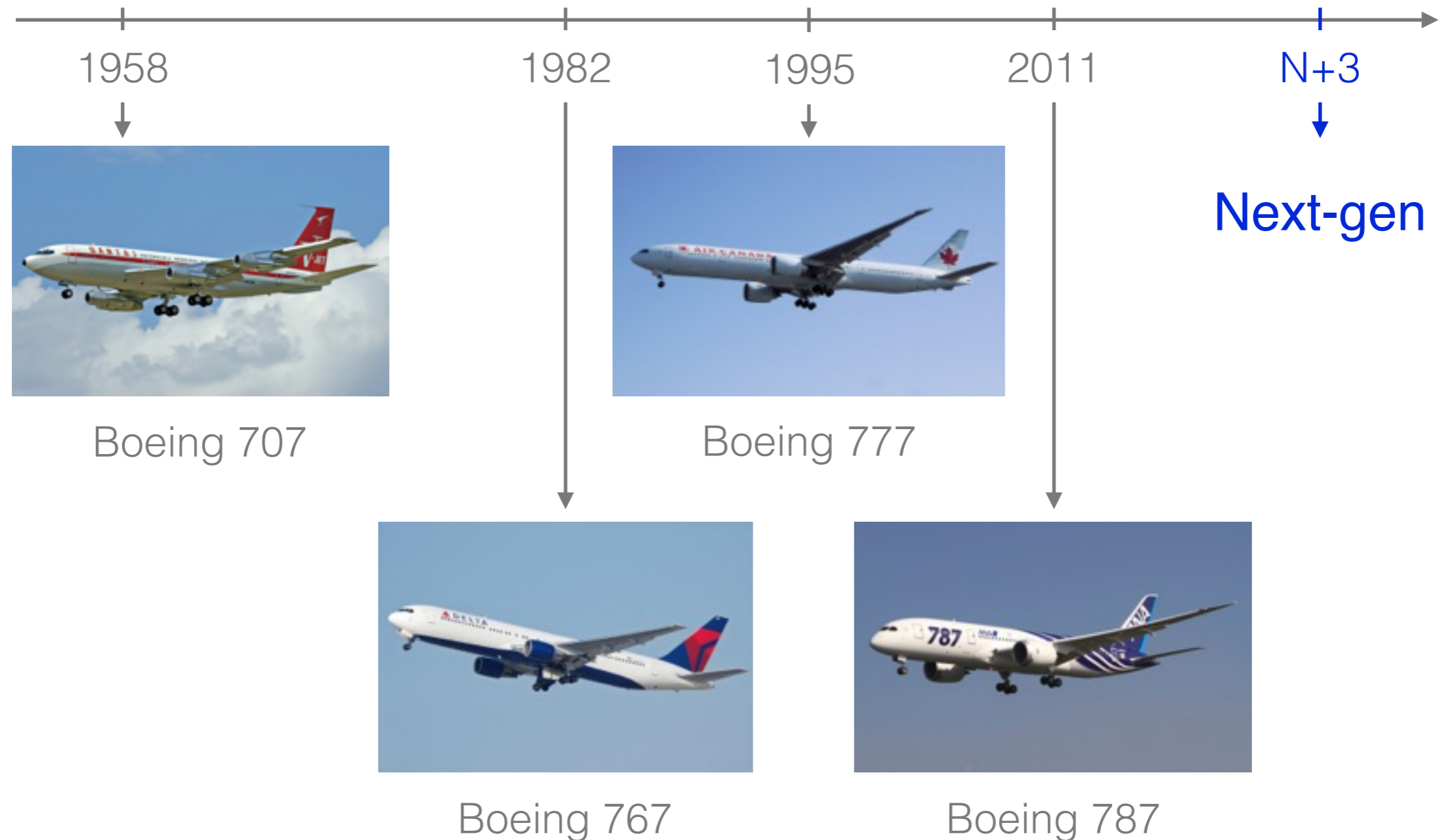
[Efficiency trends for new commercial jet aircraft. ICCT, 2009]

# Commercial aircraft designs have begun to plateau in fuel efficiency



[Efficiency trends for new commercial jet aircraft. ICCT, 2009]

# The tube-and-wing configuration has been perfected over the last 50 years



# Breakthrough improvements require unconventional aircraft configurations



Truss-braced wing



Blended wing body

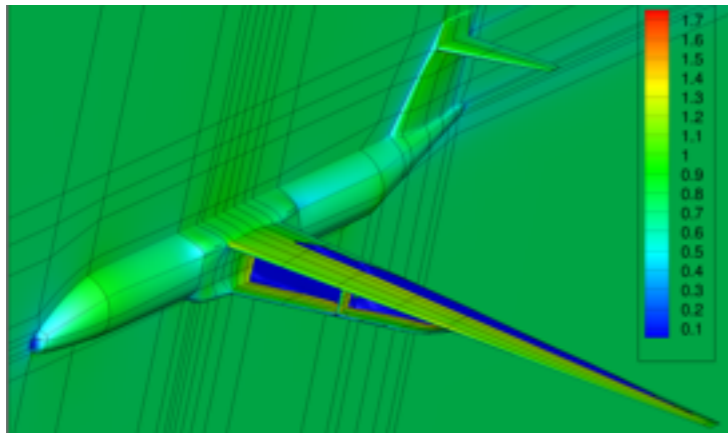


Joined wing



Double bubble

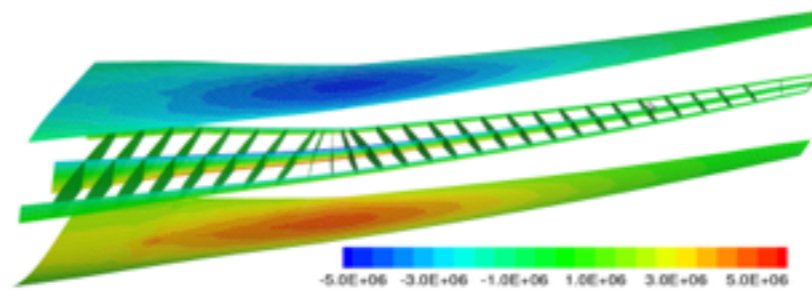
# Low-fidelity and empirical design tools do not adequately model the tradeoffs



Additional wave and interference drag



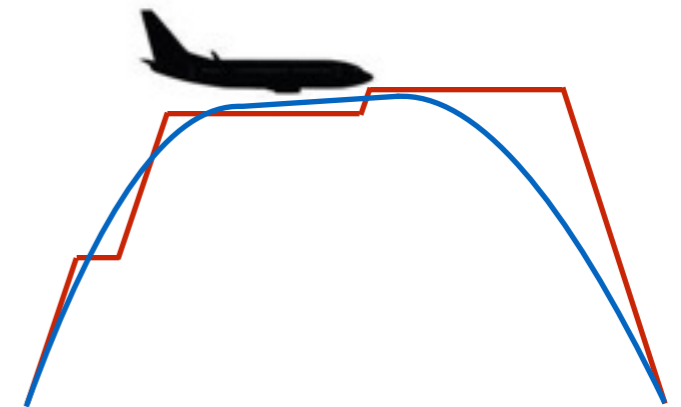
CFD analysis



High aspect-ratio composite wings



Aeroelastic tailoring

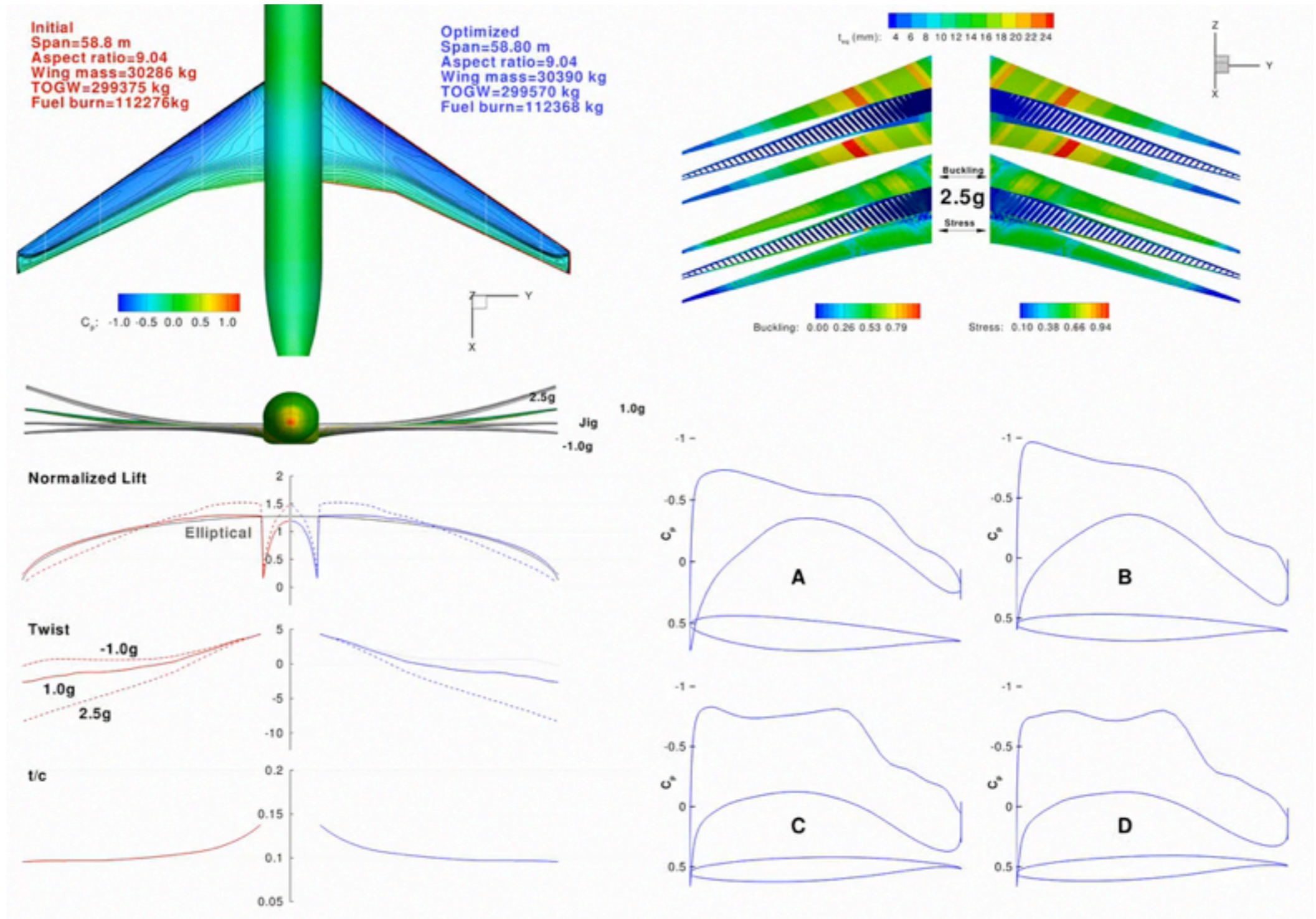


Continuous descent and low Mach number flight



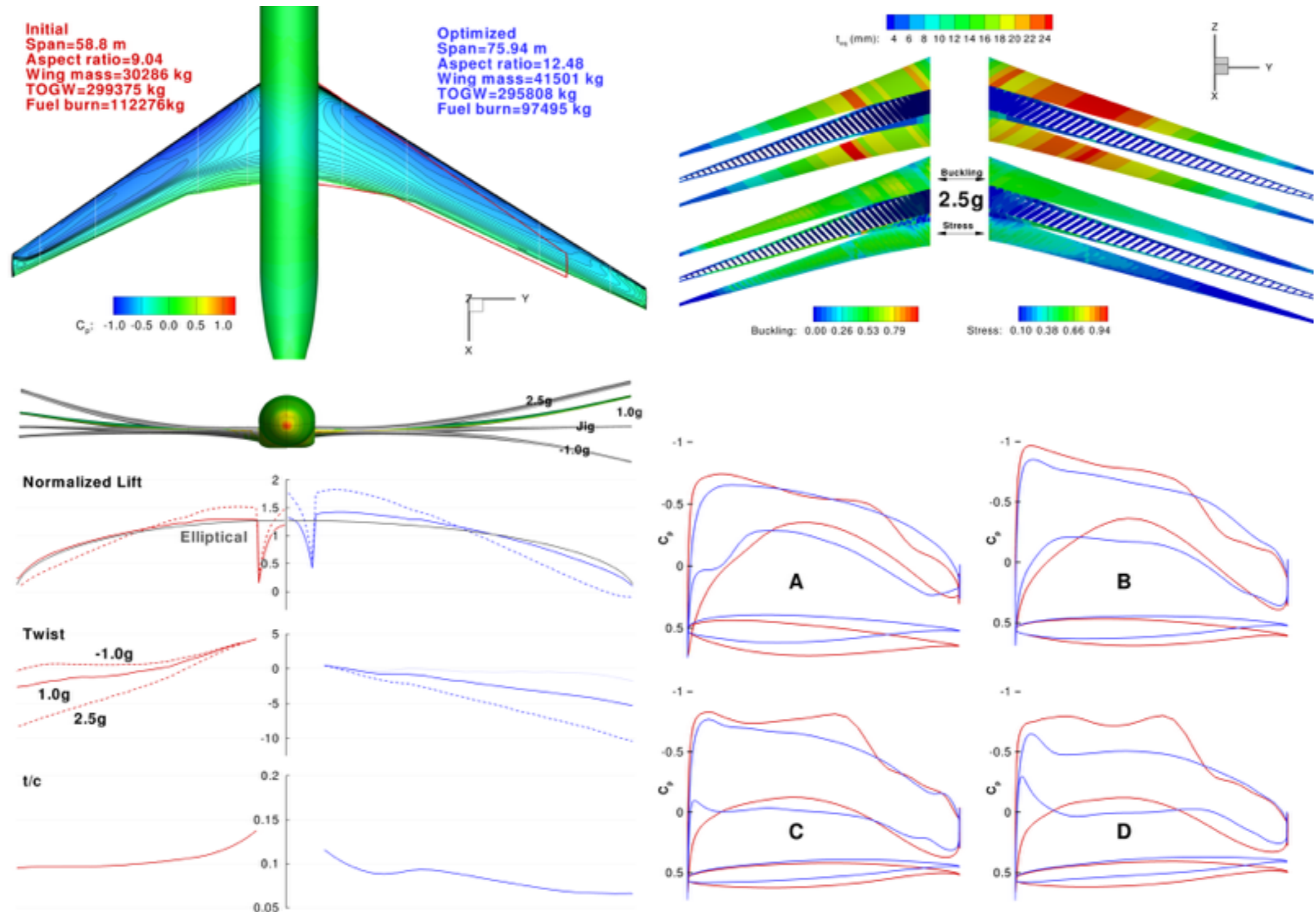
Mission analysis

# Adjoint-based design optimization algorithms can accelerate the design process



[Kenway, Kennedy, and Martins, AIAA 2014-3274]

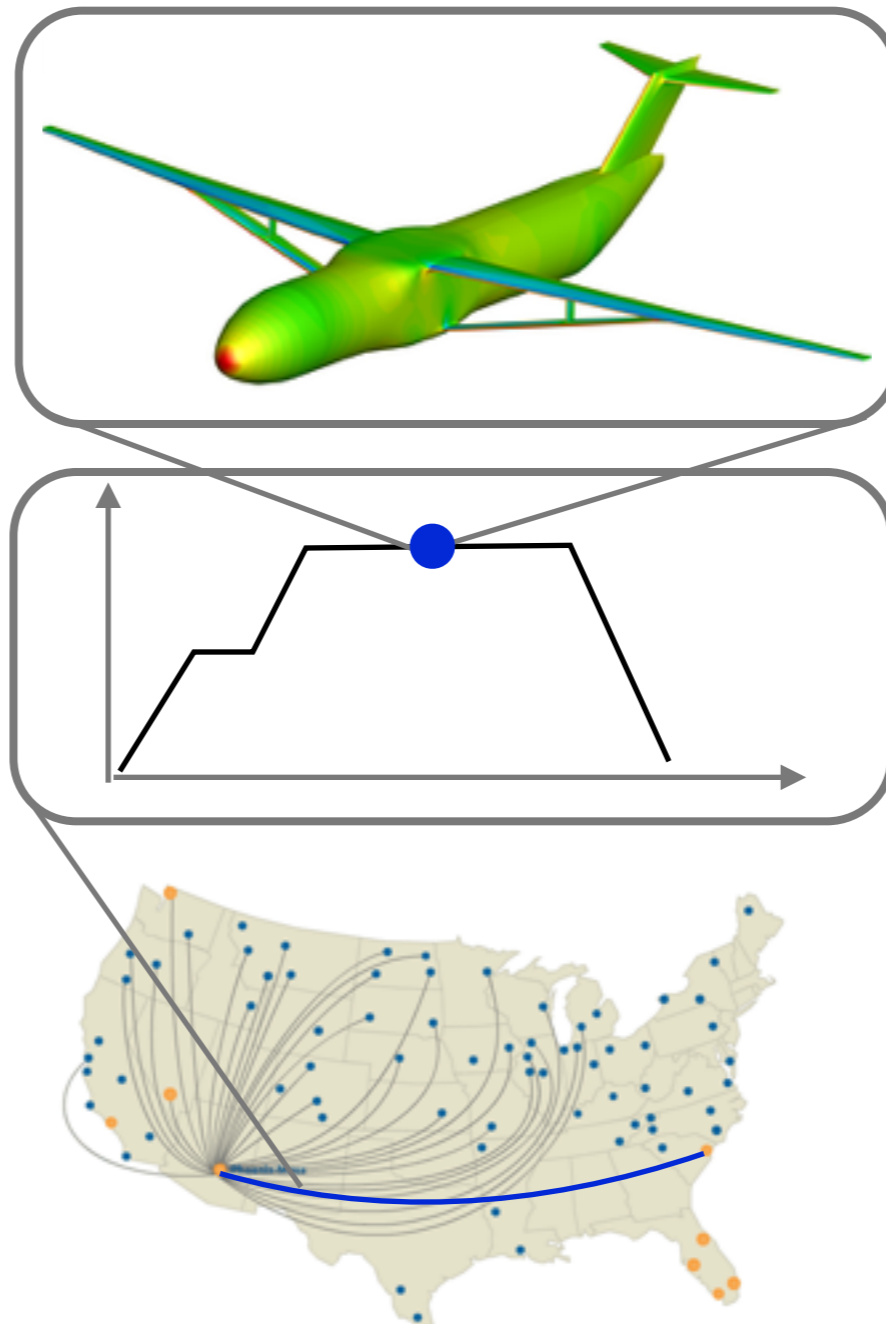
# Adjoint-based design optimization algorithms can accelerate the design process



[Kenway, Kennedy, and Martins, AIAA 2014-3274]

## The challenge problem:

How can we design a new configuration while considering the impact at the airline level?



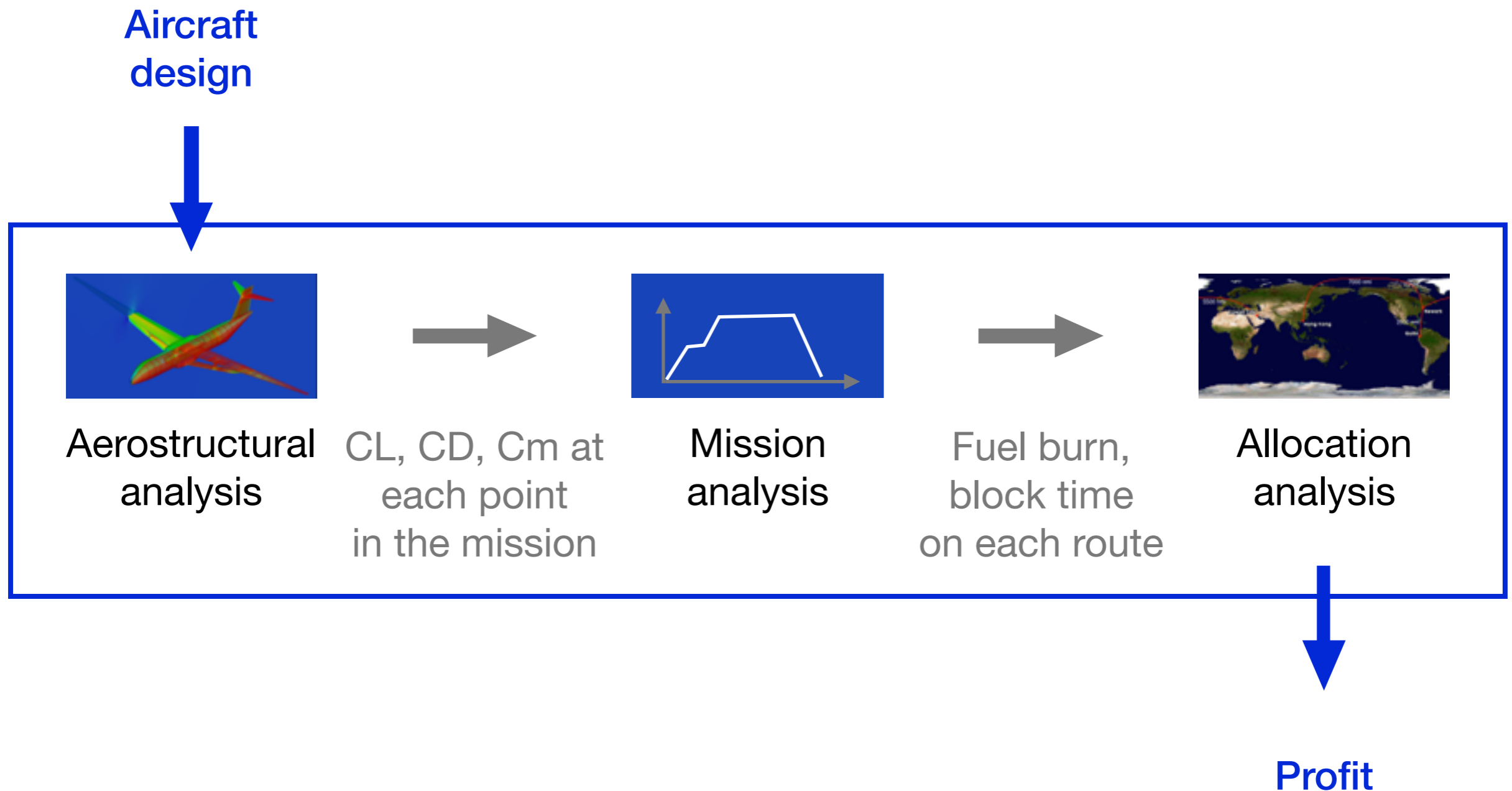
# We chose to focus on the truss-braced wing



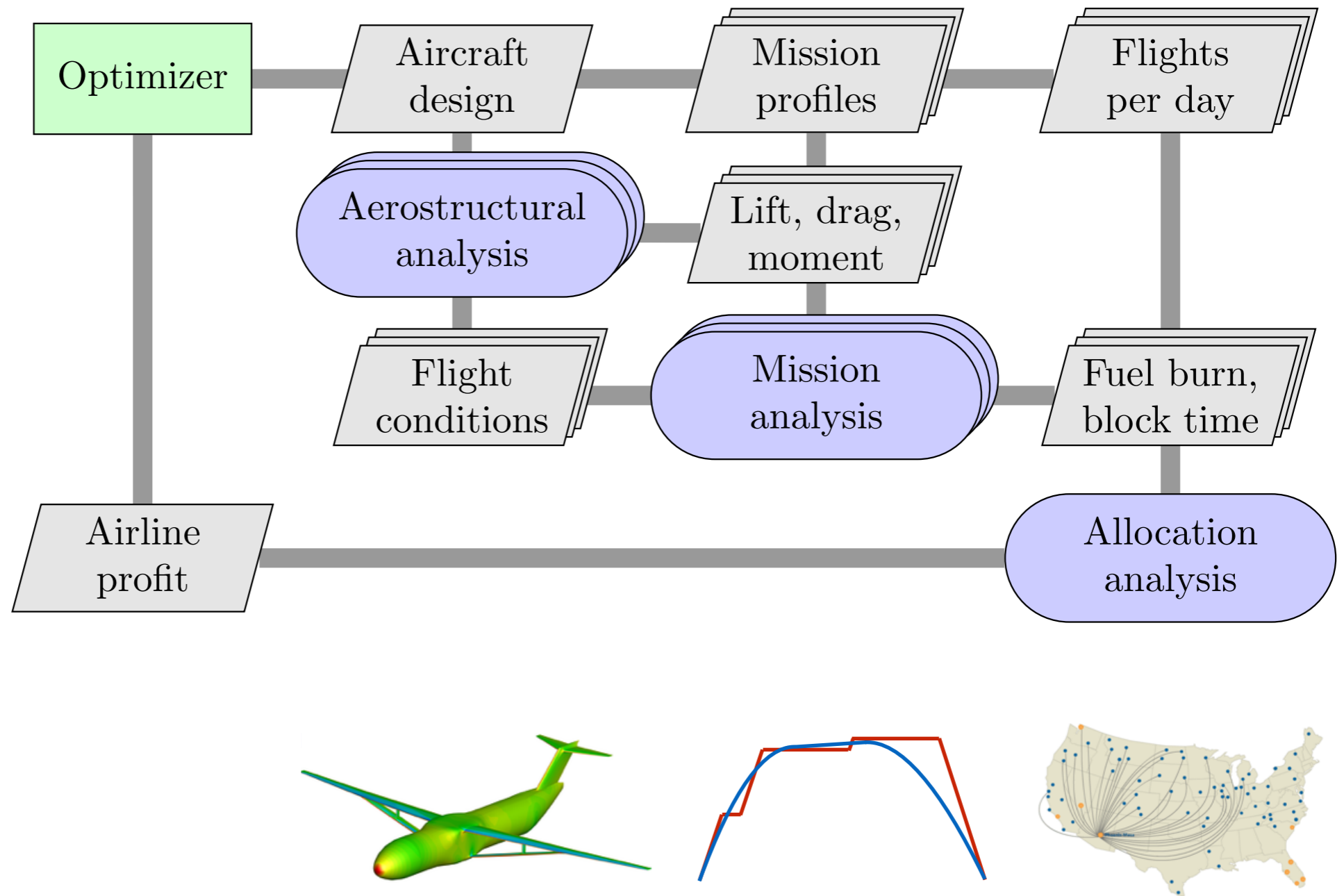
Struts to brace  
the wing  
Lighter wing

High aspect-  
ratio wings  
Lower drag

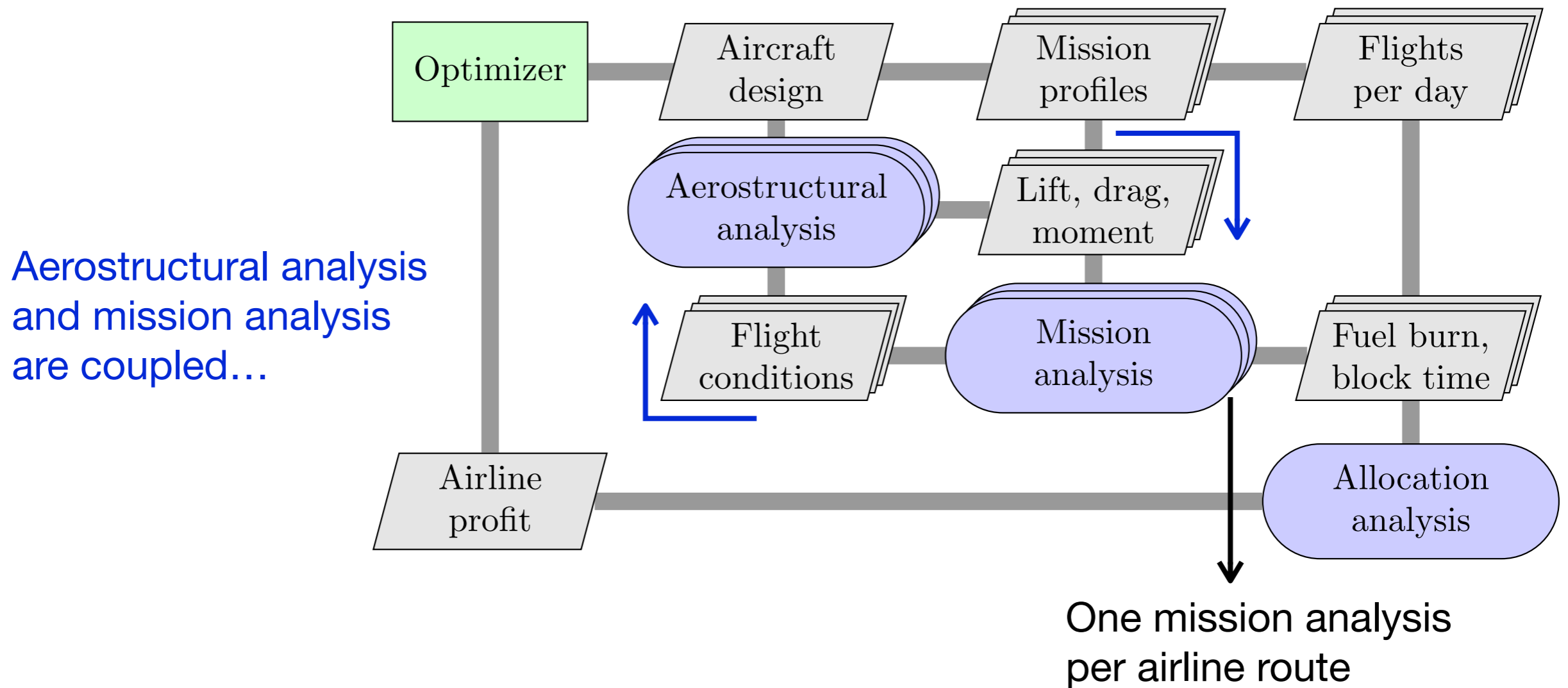
# The approach is to find the best design that maximizes profit for the airline



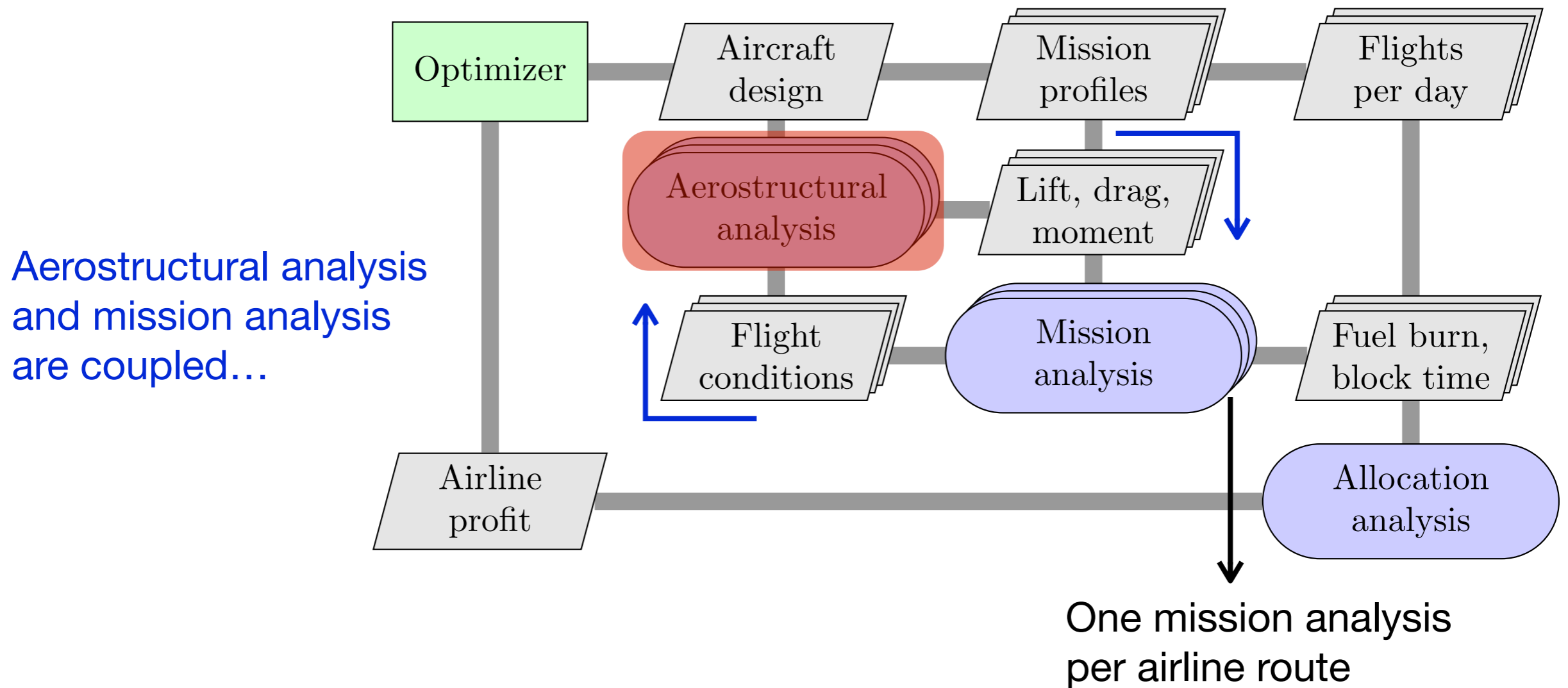
**To do this, we perform simultaneous allocation-mission-design optimization**



# To do this, we perform simultaneous allocation-mission-design optimization

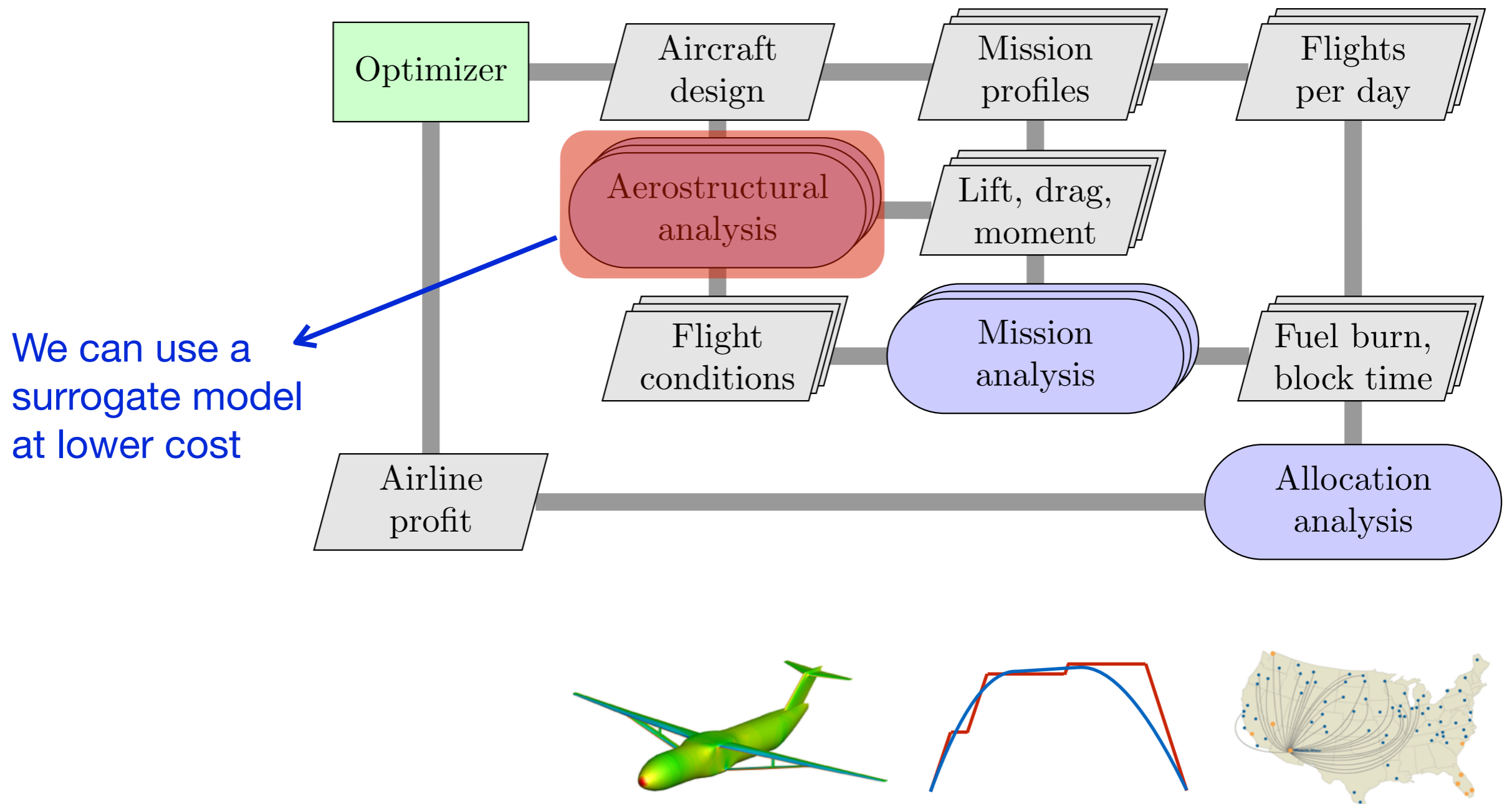


# To do this, we perform simultaneous allocation-mission-design optimization



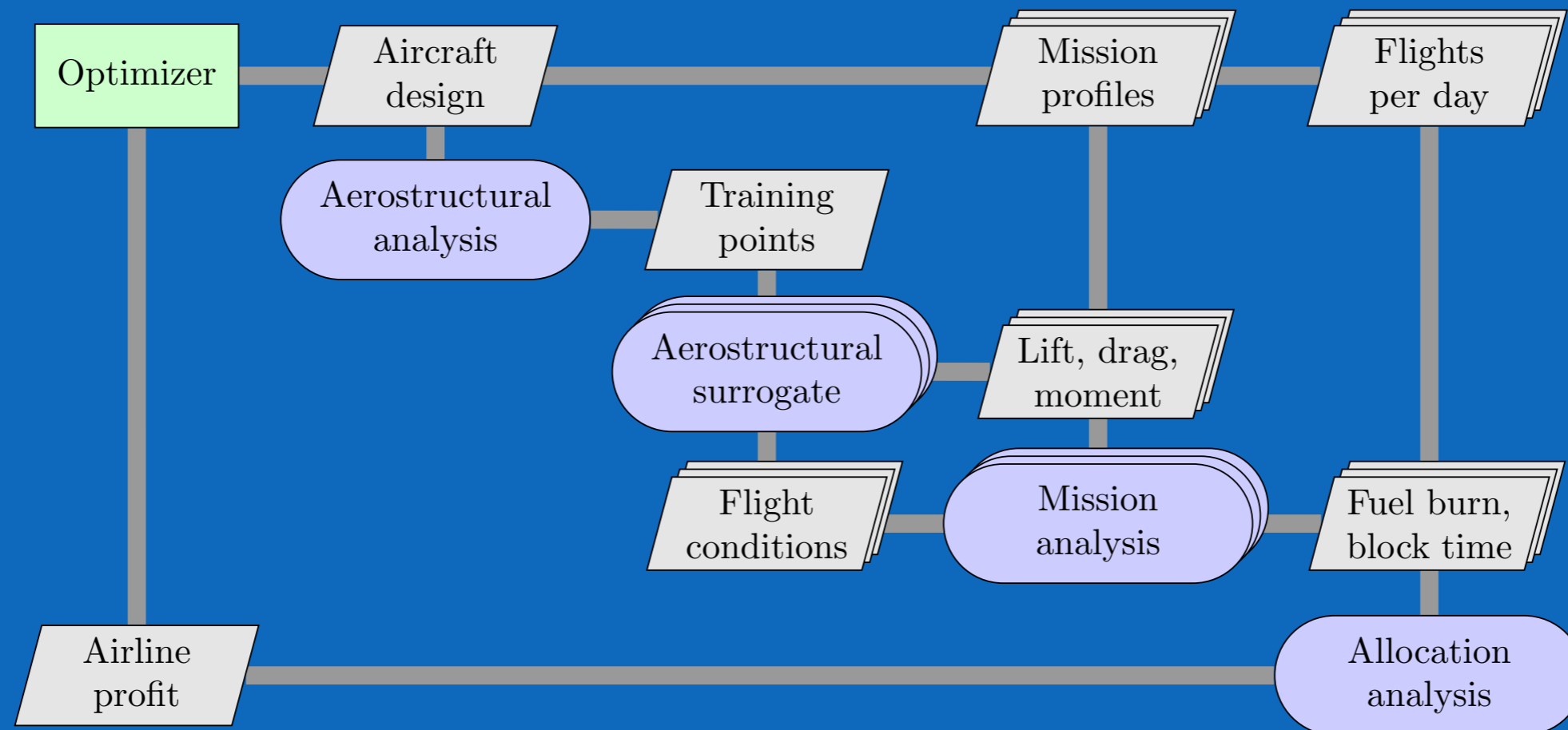
... but aerostructural analysis is computationally expensive

# Our proposed solution is to use surrogate modeling



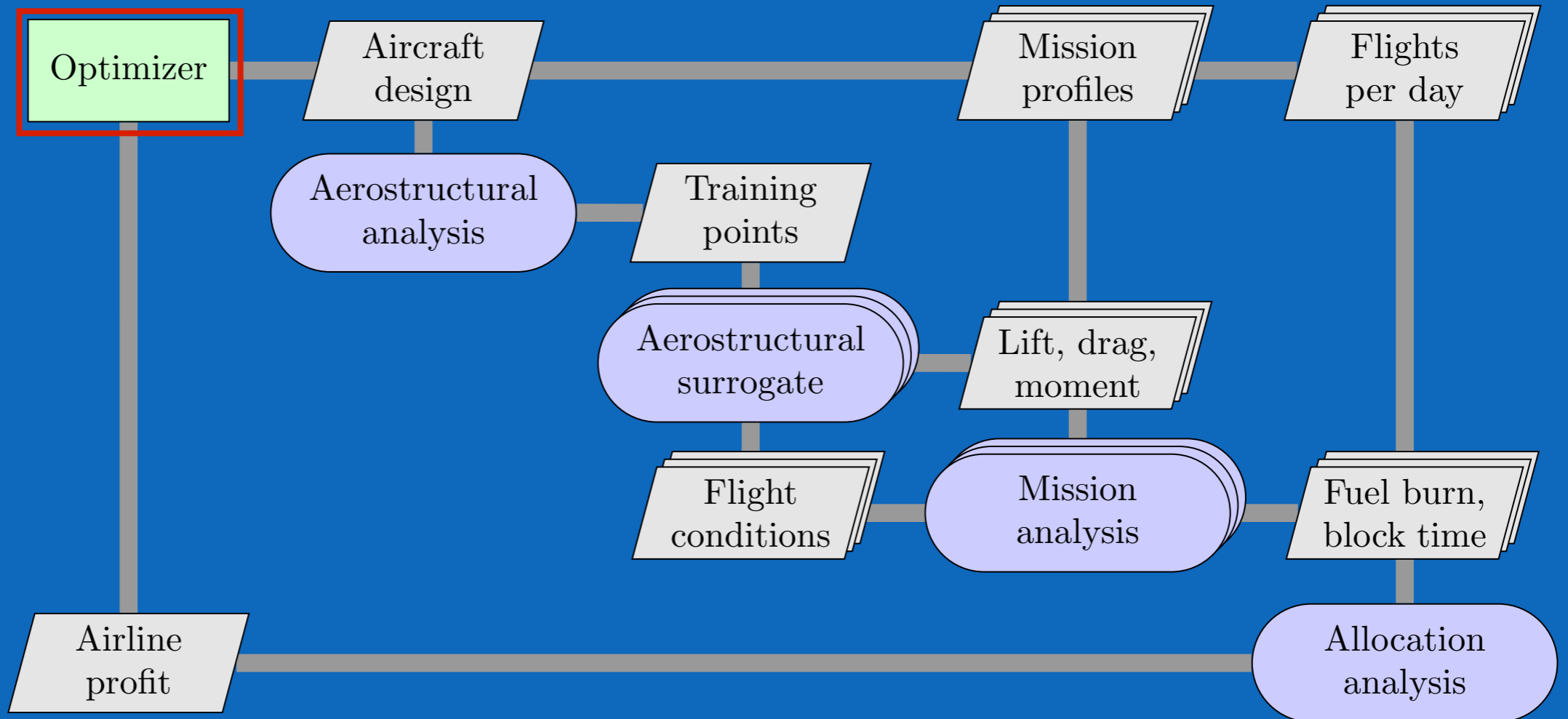
# Subprojects for Year 1

1. Parallel matrix-free optimizer
2. Parallel computational framework
3. Aerostructural modeling and optimization of the TBW
4. Mission and allocation modeling and optimization
5. Uncertainty quantification for multifidelity design



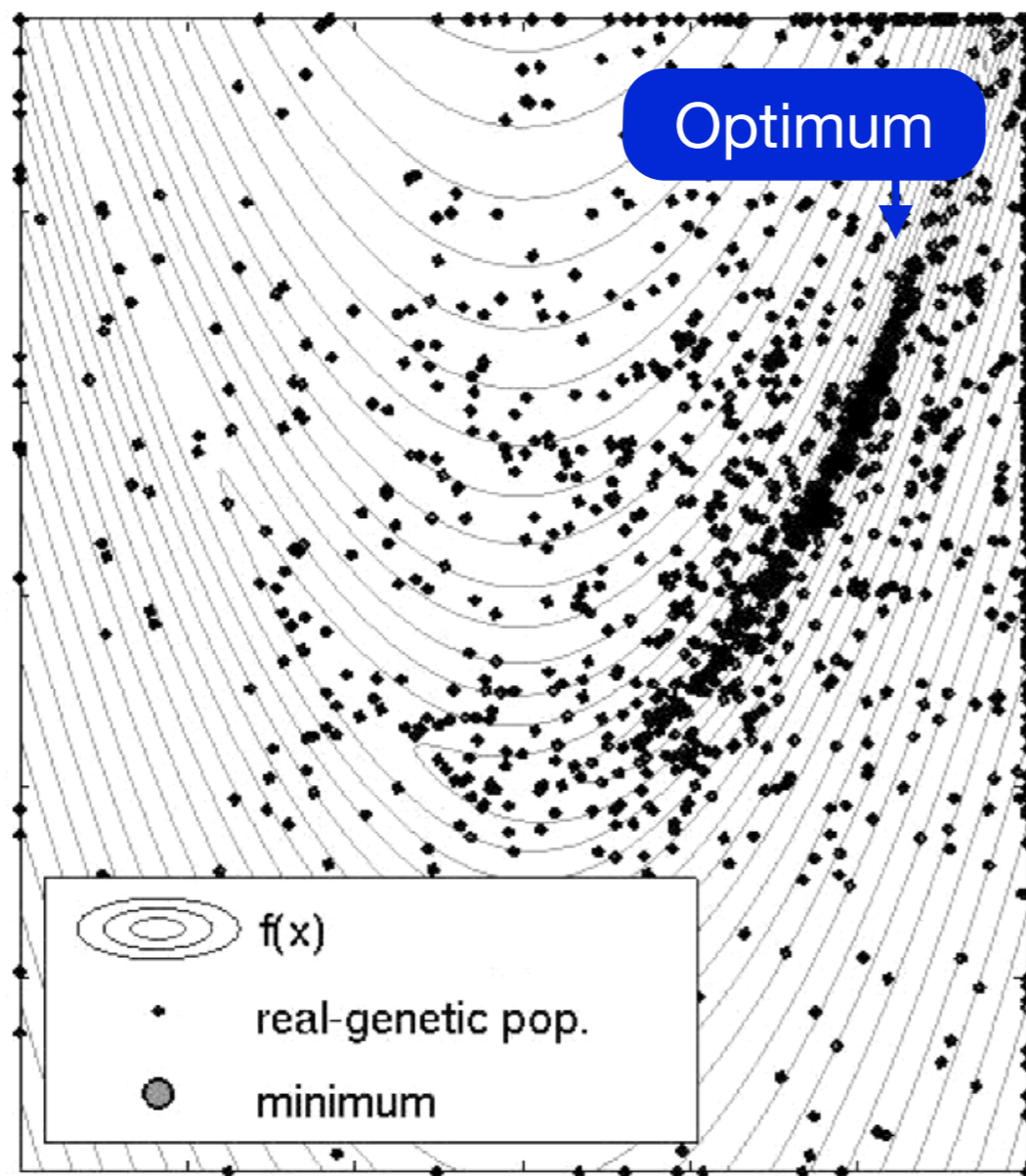
# Subproject 1

# Parallel numerical optimization

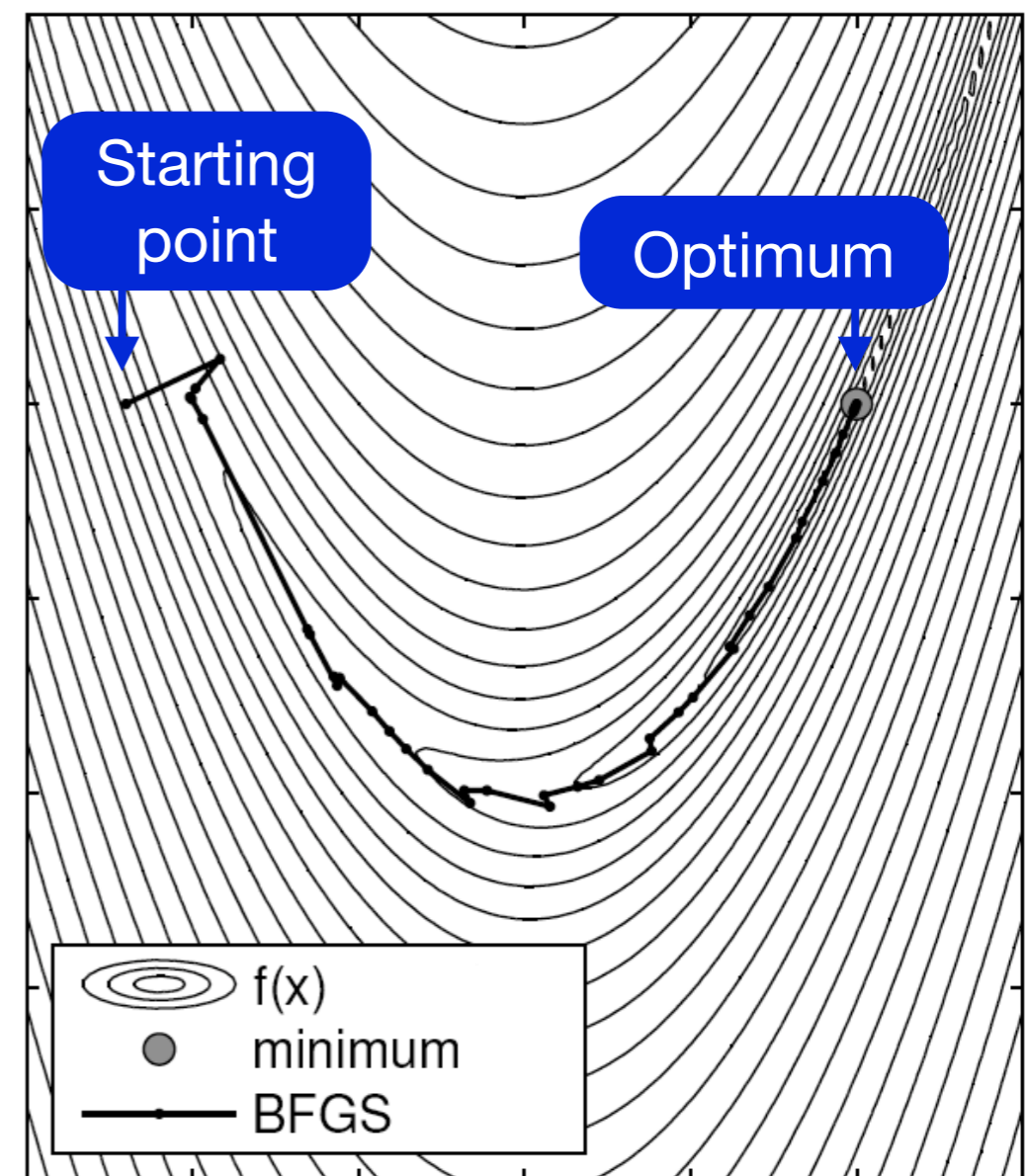


# Gradient-based optimization takes a more direct route to the optimum

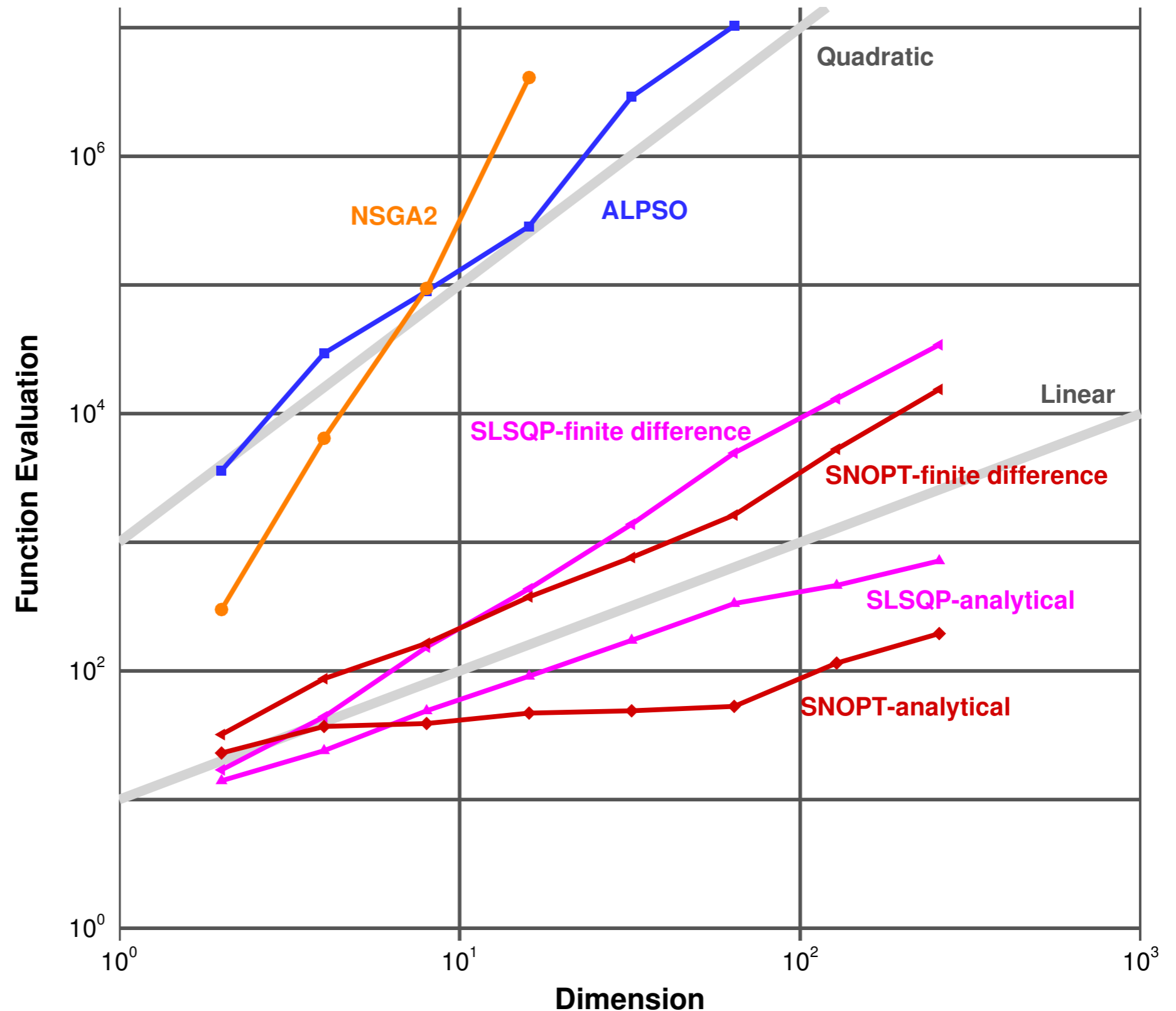
Gradient-free optimizer



Gradient-based optimizer



# Gradient-based optimization is the only hope for large numbers of design variables

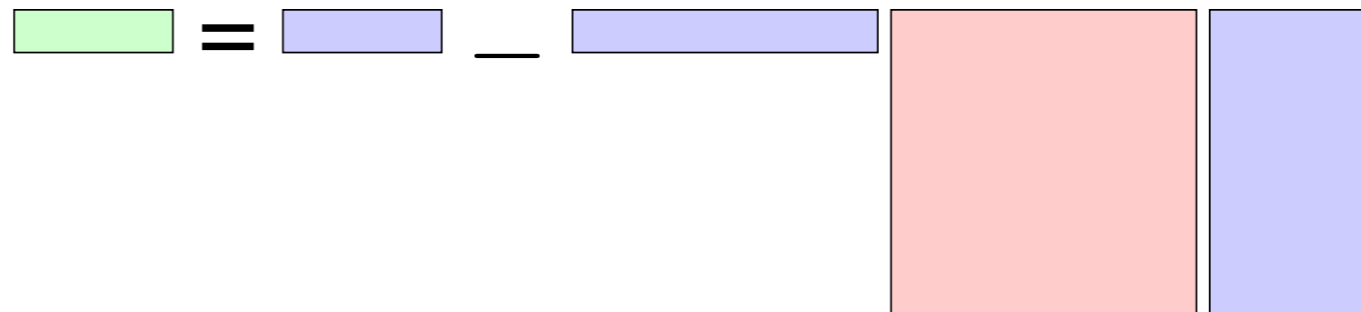


The adjoint method computes gradients with respect to large numbers of variables efficiently

$$\frac{df}{dx} = \frac{\partial f}{\partial x} - \underbrace{\frac{\partial f}{\partial y} \left[ \frac{\partial R}{\partial y} \right]^{-1}}_{\psi} \frac{\partial R}{\partial x}$$

- dy / dx

Large numbers of  
design variables

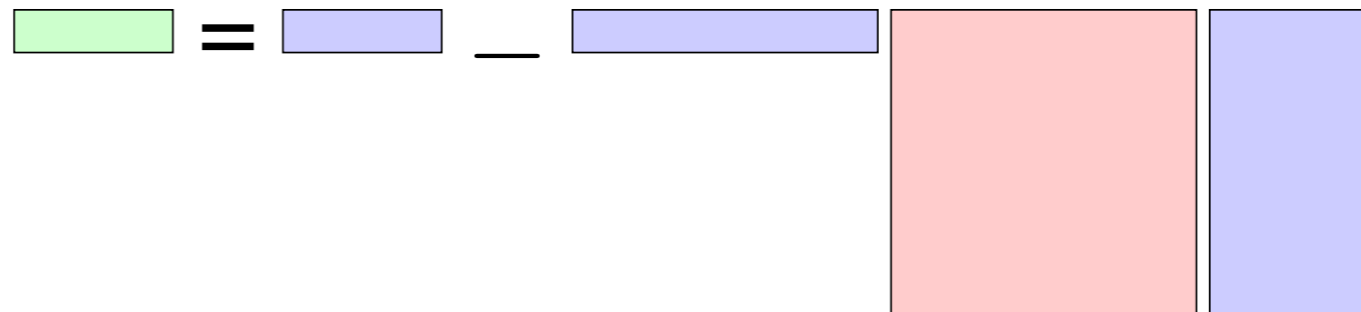


... but the adjoint method cannot handle large numbers of variables and constraints simultaneously

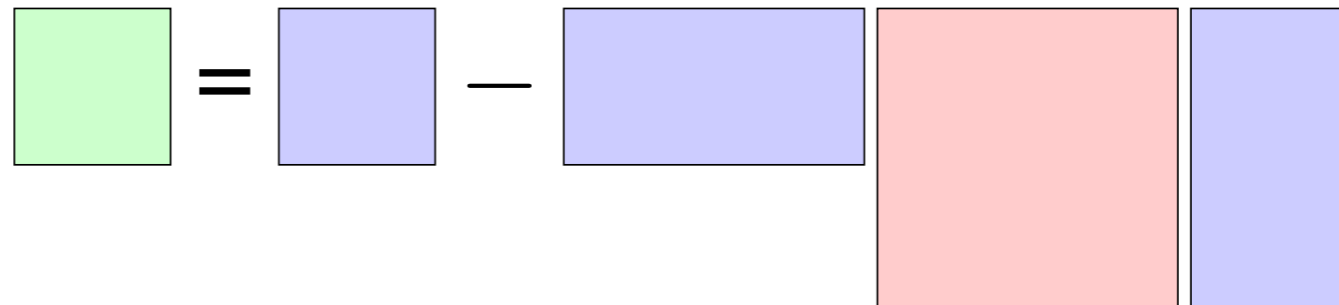
$$\frac{df}{dx} = \frac{\partial f}{\partial x} - \underbrace{\frac{\partial f}{\partial y} \left[ \frac{\partial R}{\partial y} \right]^{-1}}_{\psi} \frac{\partial R}{\partial x}$$

- dy / dx

Large numbers of  
design variables



Large numbers of  
design variables and  
constraints



# Current state-of-the-art optimizers do not scale well with problem size...

...they solve the optimality conditions using Newton's method

$$\begin{bmatrix} W_k & A_k^T \\ A_k & 0 \end{bmatrix} \begin{bmatrix} p \\ d \end{bmatrix} = - \begin{bmatrix} g_k \\ c_k \end{bmatrix}$$

This requires the matrices  $W$  and  $A$  explicitly, which are costly to compute for large problems

# We developed an all new algorithm for numerical optimization that uses a matrix-free approach

Instead of requiring the matrices explicitly, our optimizer requires only matrix-vector products

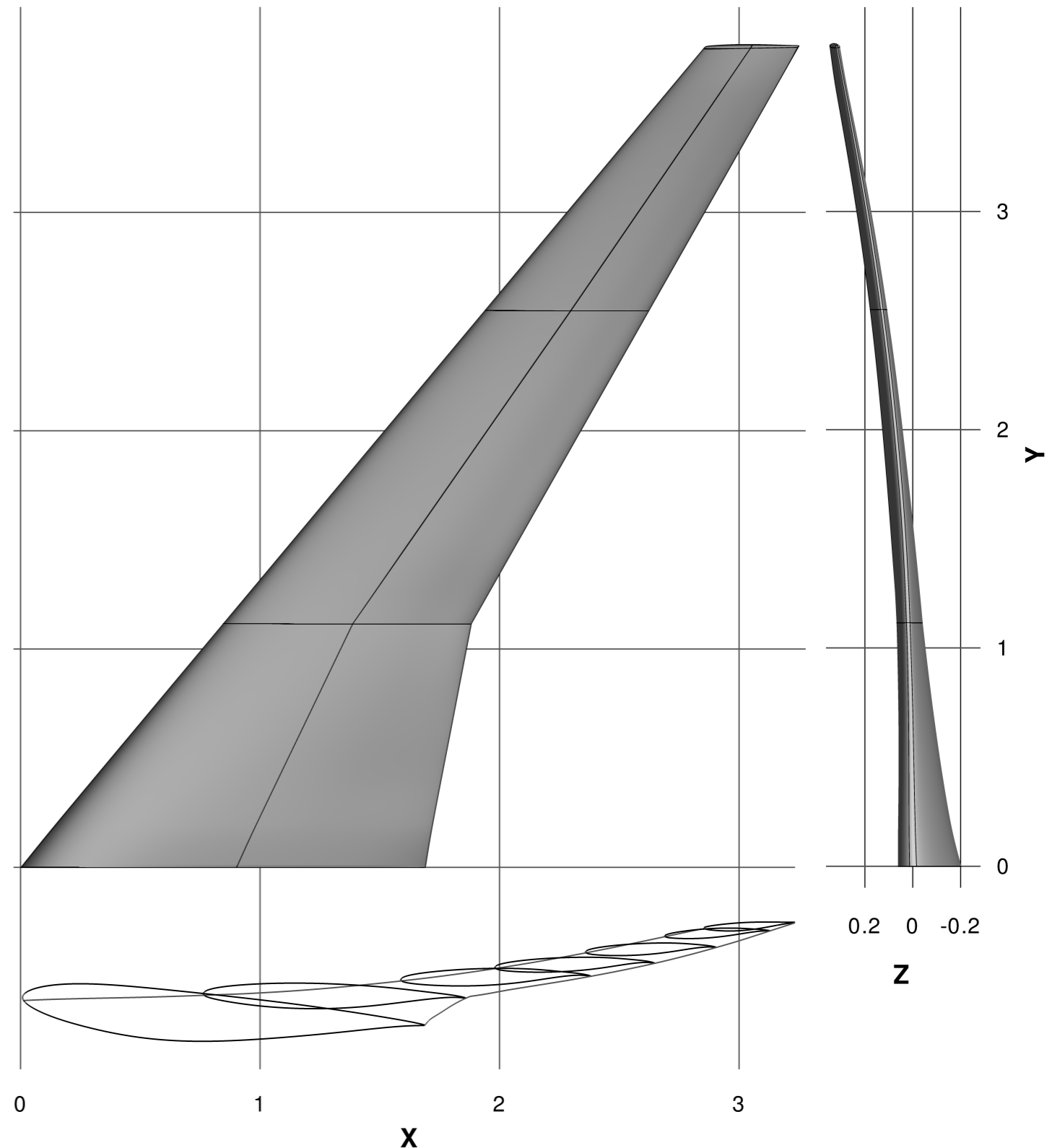
$$\begin{bmatrix} W_k & A_k^T \\ A_k & 0 \end{bmatrix} \begin{bmatrix} p \\ d \end{bmatrix} = - \begin{bmatrix} g_k \\ c_k \end{bmatrix}$$

This saves memory and computational time, enabling the solution of very large problems

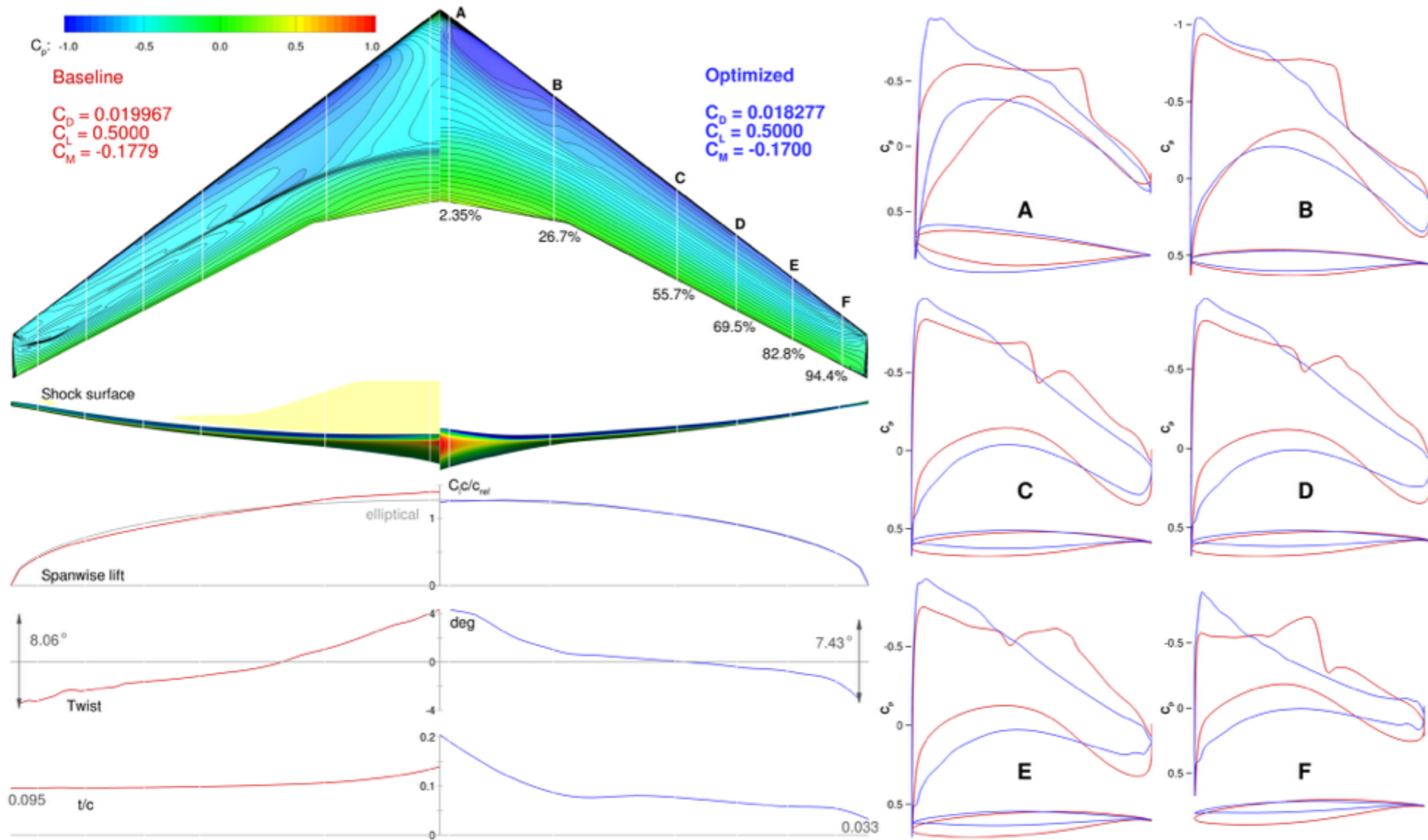
RSNK: Reduced-space Newton—Krylov

# We benchmark this new algorithm on an aerodynamic shape optimization problem

minimize drag coefficient  
with respect to airfoil shapes  
subject to lift constraint  
moment constraint  
volume constraint  
thickness constraints



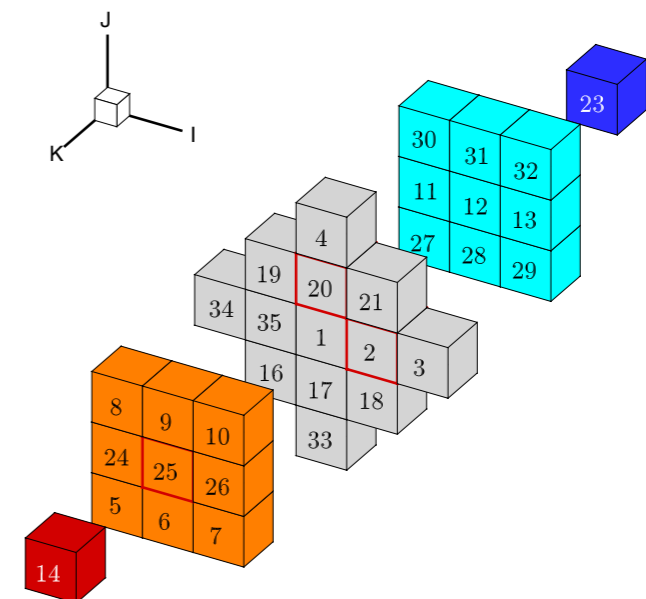
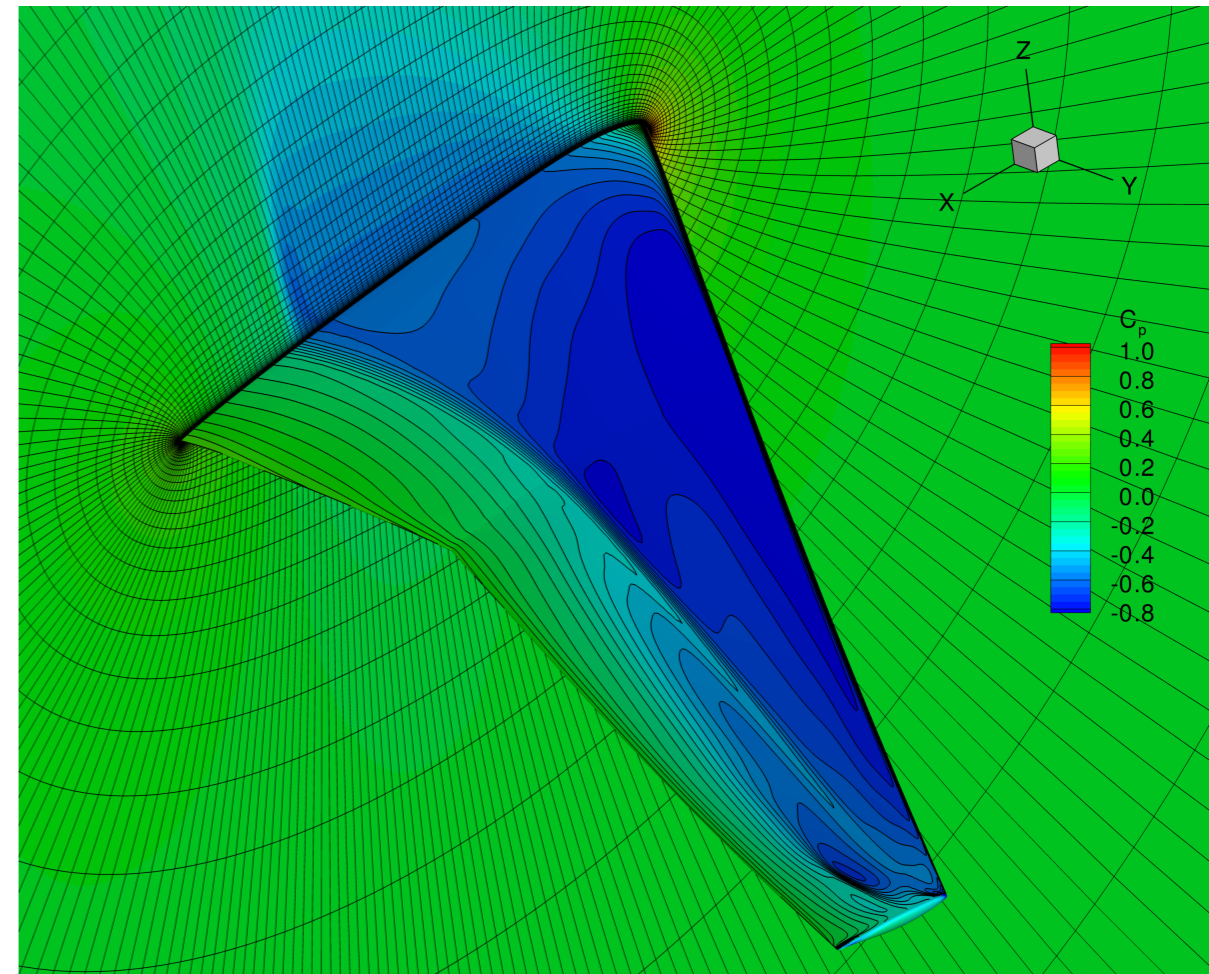
# Previous results with conventional optimizers show that this is a challenging problem



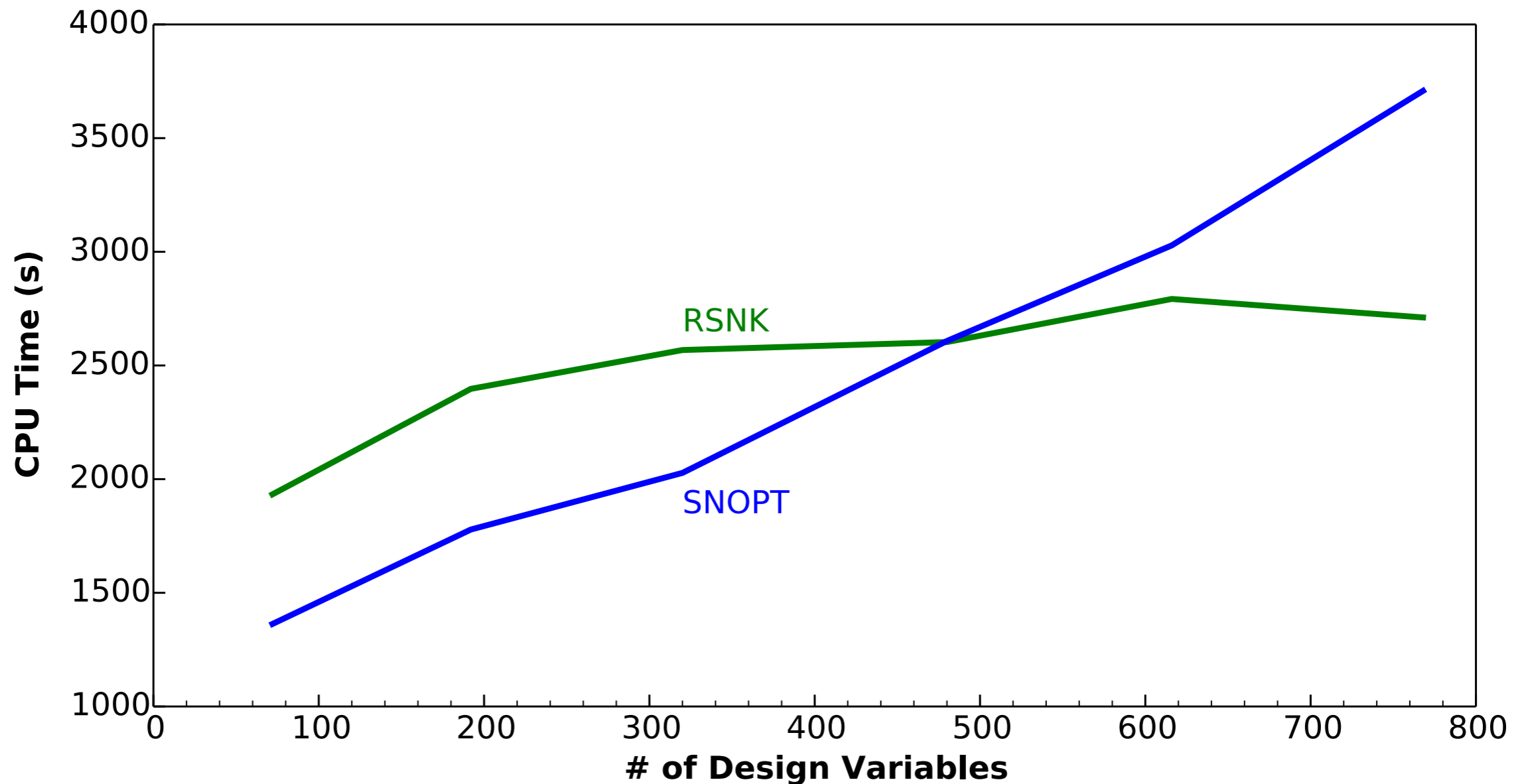
[Lyu, Kenway and Martins, 2015]

# A matrix-free interface was developed for our CFD solver and adjoint

- ▶ SUMad (based on SUmb)
- ▶ Parallel, finite-volume, cell-centered, multiblock solver for RANS equations
- ▶ Spalart–Allmaras turbulence model
- ▶ Implemented adjoint using automatic differentiation to evaluate partial derivatives
- ▶ Developed both frozen-turbulence and full-turbulence adjoint
- ▶ **New: matrix-free interface**

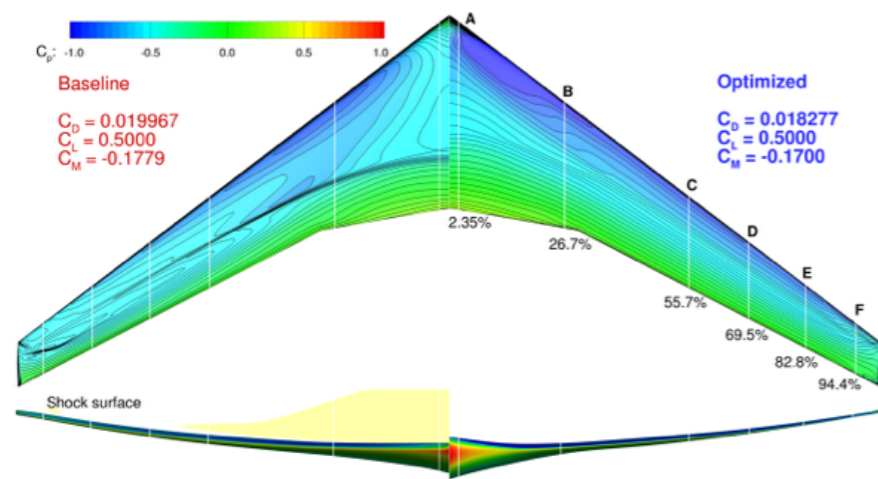


# RSNK was shown to be more efficient than a state-of-the-art optimizer for large problems



[Dener, Hicken, Kenway, Lyu and Martins, AIAA 2015-1945]

# Summary for Subproject 1

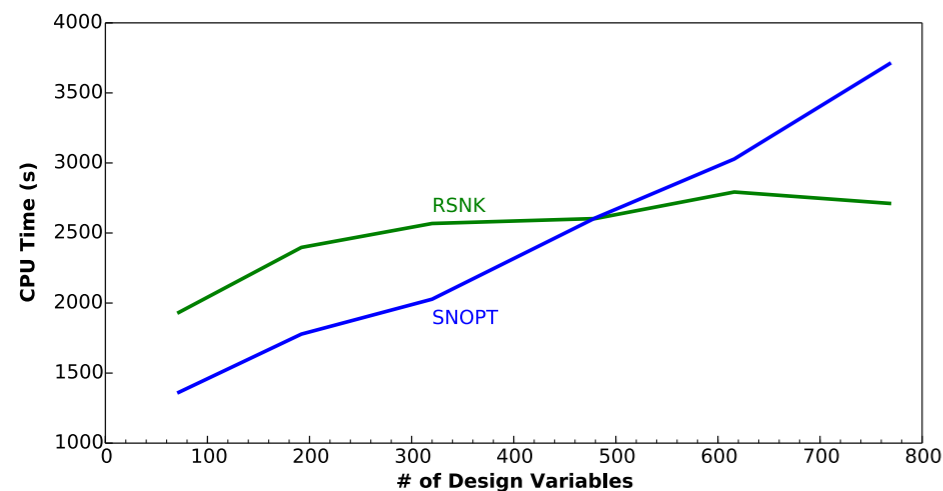


## Year 1 achievements:

- ▶ Developed a novel parallel optimizer
- ▶ Develop a matrix-free RANS CFD adjoint
- ▶ Demonstrated scaling on a high-fidelity aerodynamic shape optimization problem

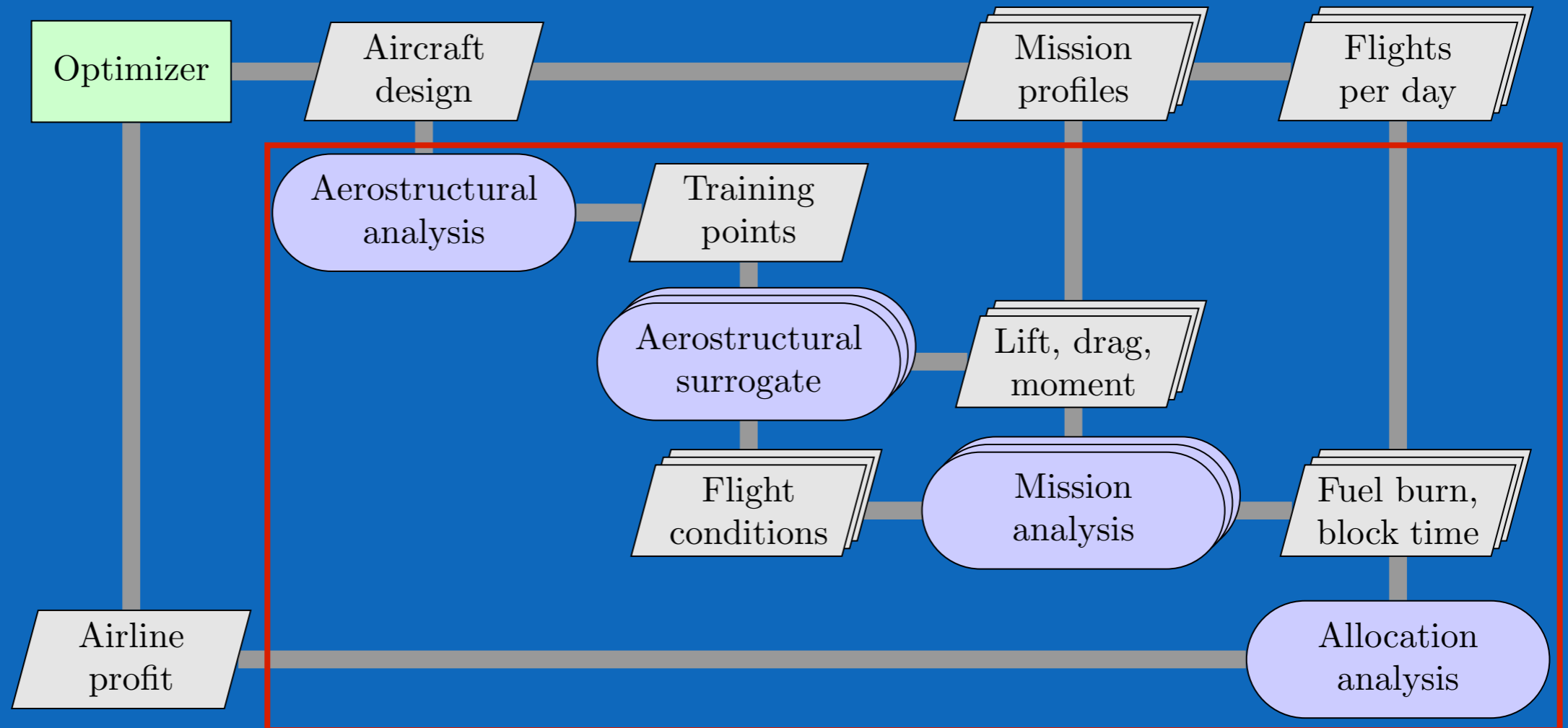
## Next steps:

- ▶ Perform RANS-based aerodynamic shape optimization
- ▶ Implement inequality constraints
- ▶ Implement matrix-free aerostructural interface

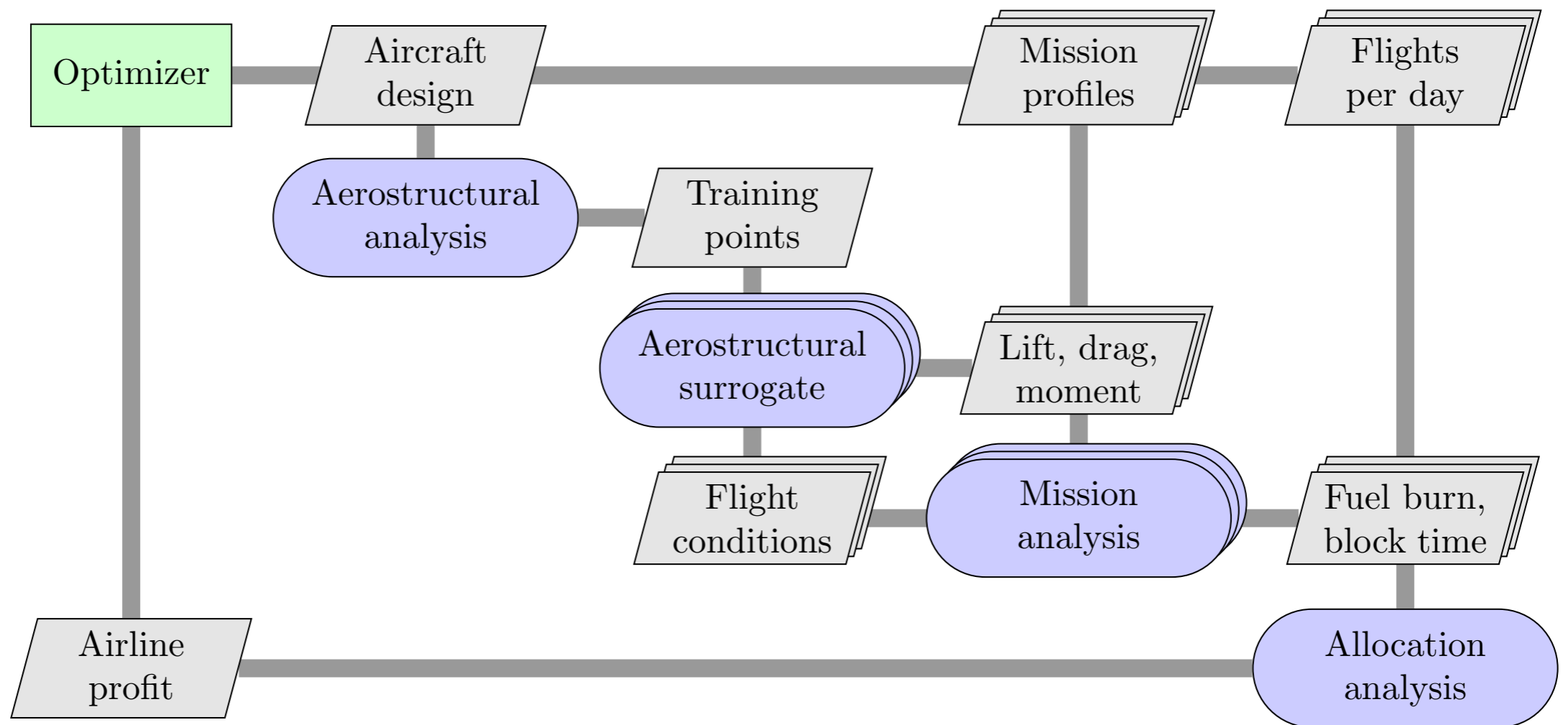


## Subproject 2

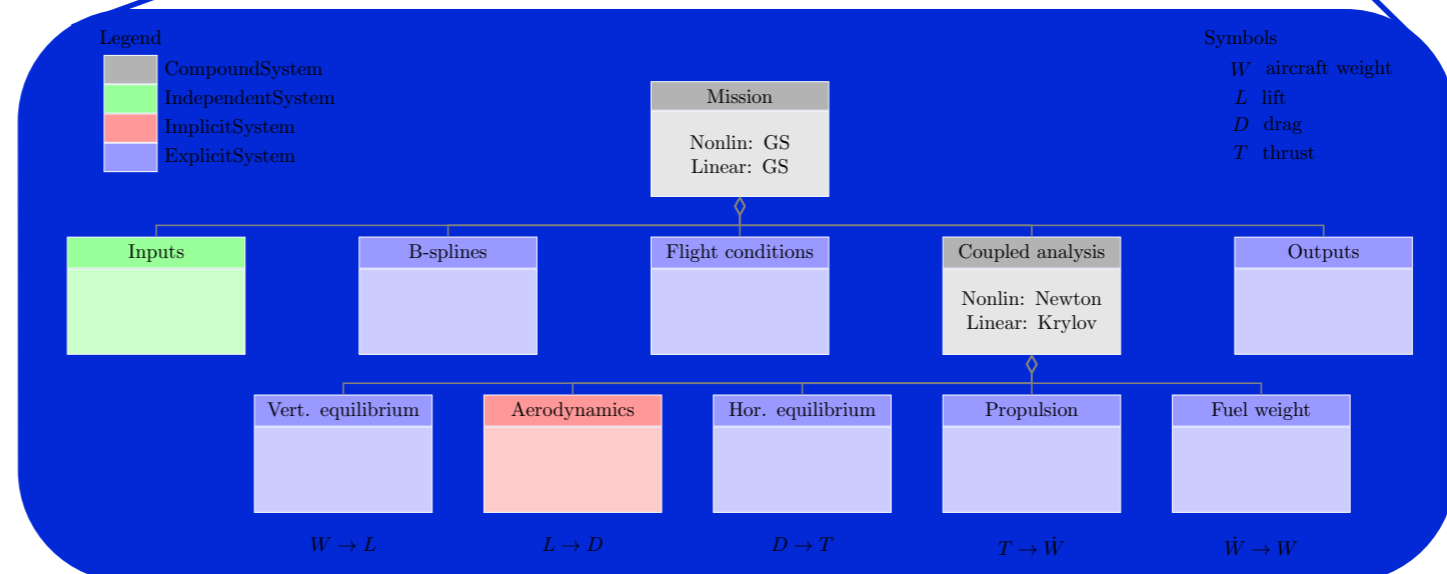
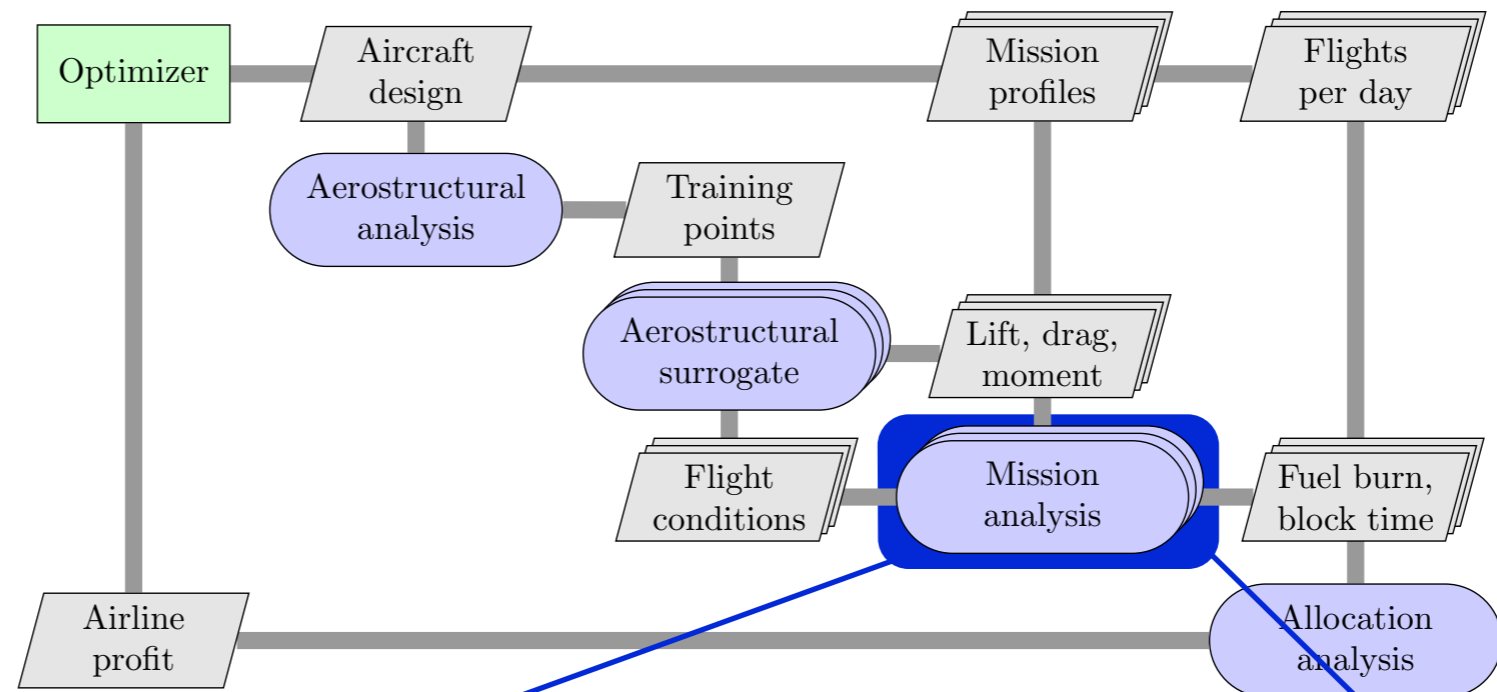
# Parallel computational framework



# Combining many types of models and computing their gradients is challenging



# Combining many types of models and computing their gradients is challenging



Subproject 4

# We recently developed an equation that unifies the methods for computing derivatives

$$\frac{\partial R}{\partial u} \frac{du}{dr} = \mathcal{I} = \left[ \frac{\partial R}{\partial u} \right]^T \left[ \frac{du}{dr} \right]^T$$

- ▶ Finite differences  $\frac{df}{dx} = \frac{\partial F}{\partial x}$
- ▶ Chain rule  $\frac{df}{dx} = \frac{\partial F}{\partial x} + \frac{\partial F}{\partial y} \frac{dy}{dx}$
- ▶ Direct method/adjoint method  $\frac{df}{dx} = \frac{\partial F}{\partial x} - \frac{\partial F}{\partial y} \frac{\partial R^{-1}}{\partial y} \frac{\partial R}{\partial x}$
- ▶ Algorithmic differentiation

Using this theory, we developed a parallel framework that computes coupled gradients

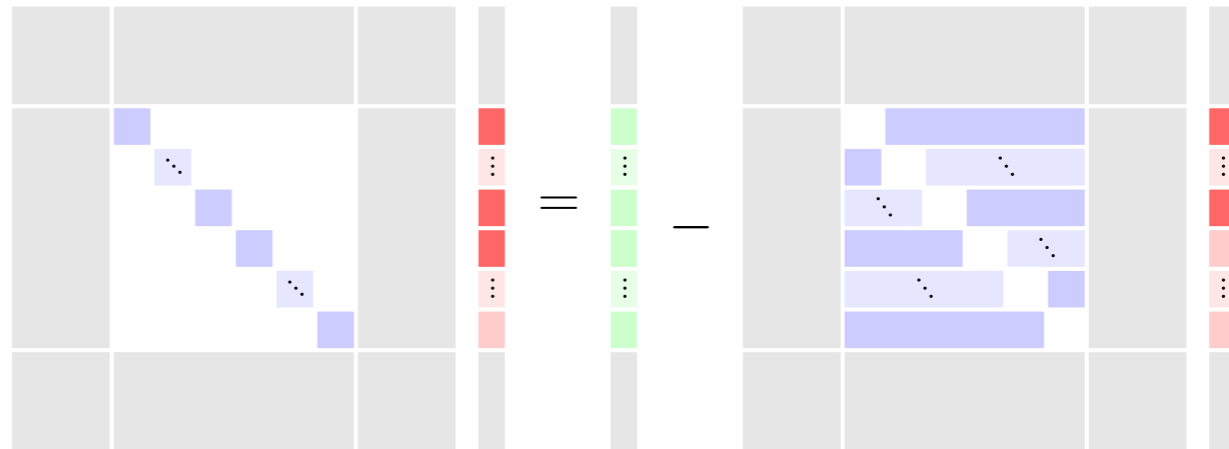
$$\begin{array}{c}
 \begin{array}{|c|} \hline \frac{\partial R_1}{\partial u} \\ \hline \vdots \\ \hline \frac{\partial R_n}{\partial u} \\ \hline \end{array}
 \end{array}
 =
 \begin{array}{|c|} \hline 0 \\ \hline \vdots \\ \hline \cancel{\mathcal{I}} \\ \hline \vdots \\ \hline 0 \\ \hline \end{array}
 \frac{\partial R}{\partial u} \frac{du}{dr} = \mathcal{I}$$
  

$$\begin{array}{c}
 \begin{array}{|c|c|c|c|c|} \hline \frac{\partial R_1}{\partial u}^T & \vdots & & \vdots & \frac{\partial R_n}{\partial u}^T \\ \hline \end{array}
 \end{array}
 =
 \begin{array}{|c|} \hline 0 \\ \hline \vdots \\ \hline \cancel{\mathcal{I}} \\ \hline \vdots \\ \hline 0 \\ \hline \end{array}
 \frac{\partial R}{\partial u}^T \frac{du}{dr}^T = \mathcal{I}$$

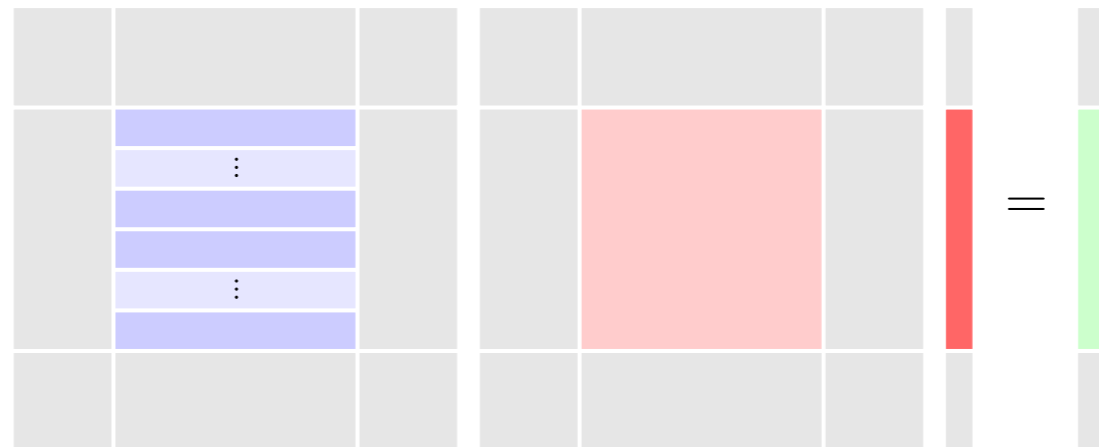
Each component computes its local derivatives;  
the framework computes coupled gradients automatically

# The framework uses efficient numerical linear algebra

Block Gauss-Seidel



Preconditioned  
Krylov subspace methods



The built-in solvers are used extensively  
in the mission analysis component

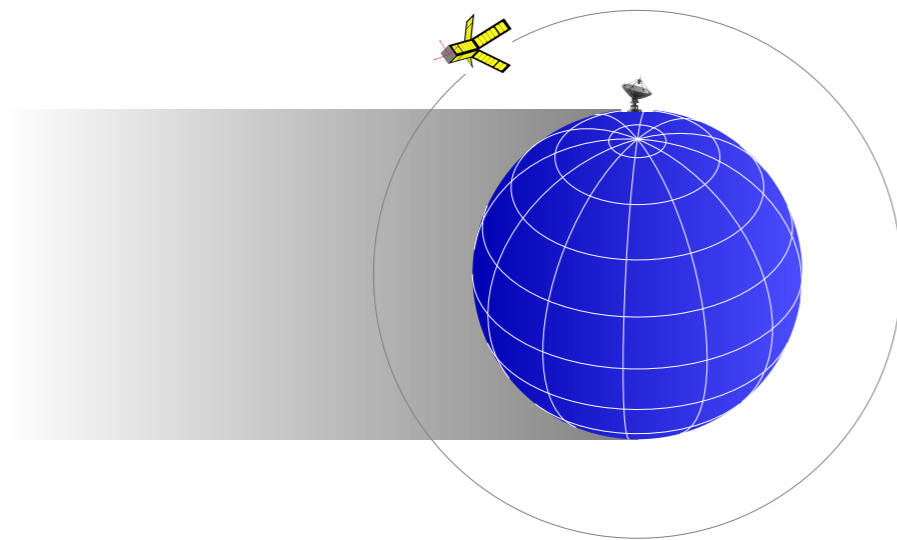
[Hwang and Martins, 2015 (to be submitted)]

# This algorithmic framework has been implemented in NASA's OpenMDAO



Several other applications have been handled:

Satellite design and  
operation optimization

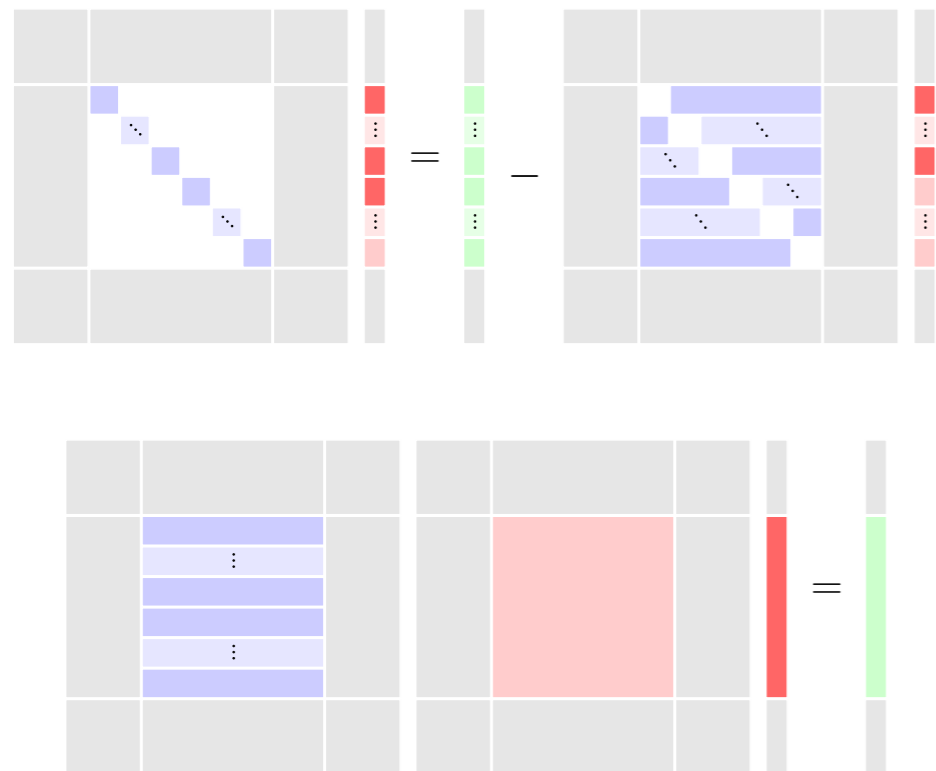


Wind turbine optimization



[Gray, Hearn, Moore, Hwang, Martins, and Ning, AIAA 2014-2042]

# Summary for Subproject 2



## Year 1 achievements:

- ▶ Developed a novel algorithmic framework for coupled analysis and gradient computation
- ▶ Implemented framework numerical methods in OpenMDAO
- ▶ Successful spin-offs through OpenMDAO

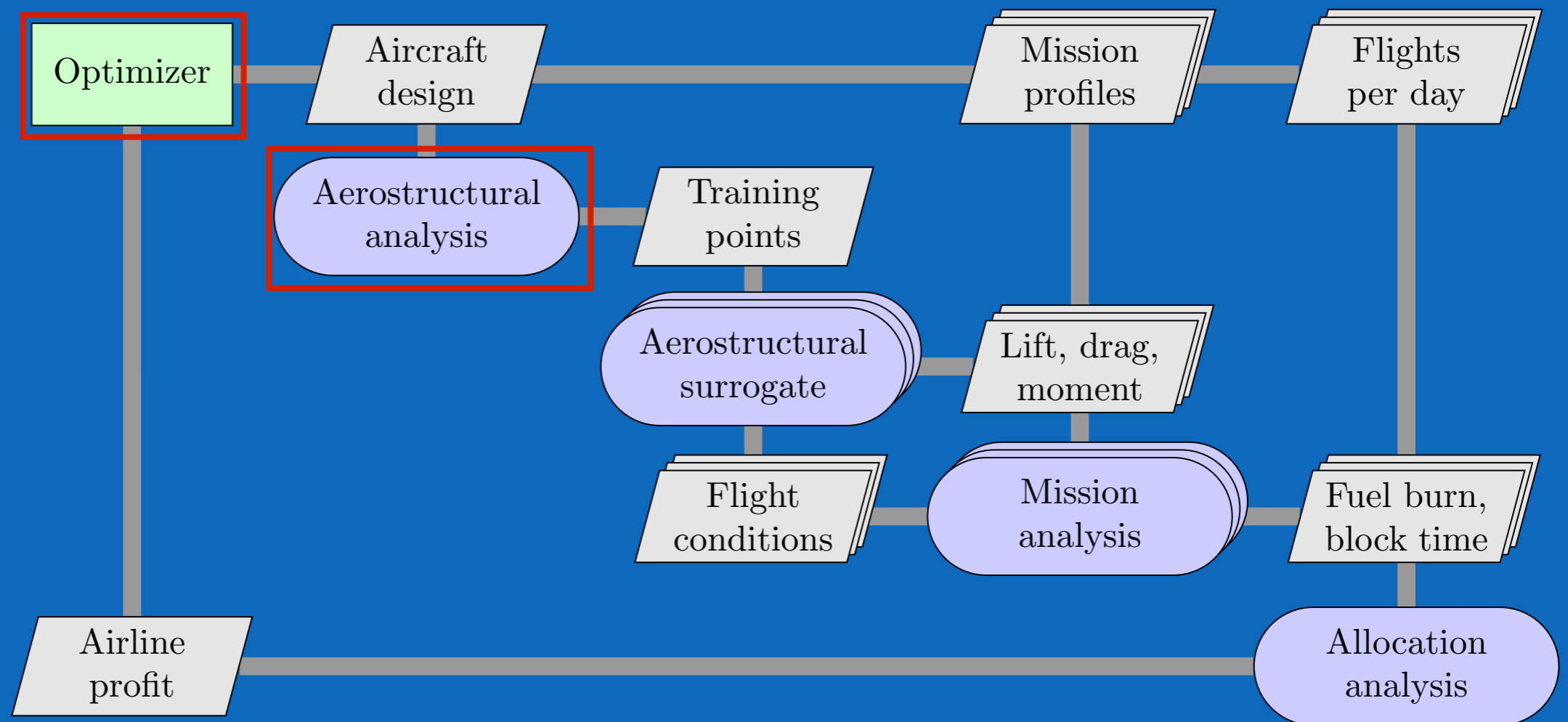
## Next steps:

- ▶ Benchmark framework in other problems
- ▶ Continue supporting OpenMDAO team

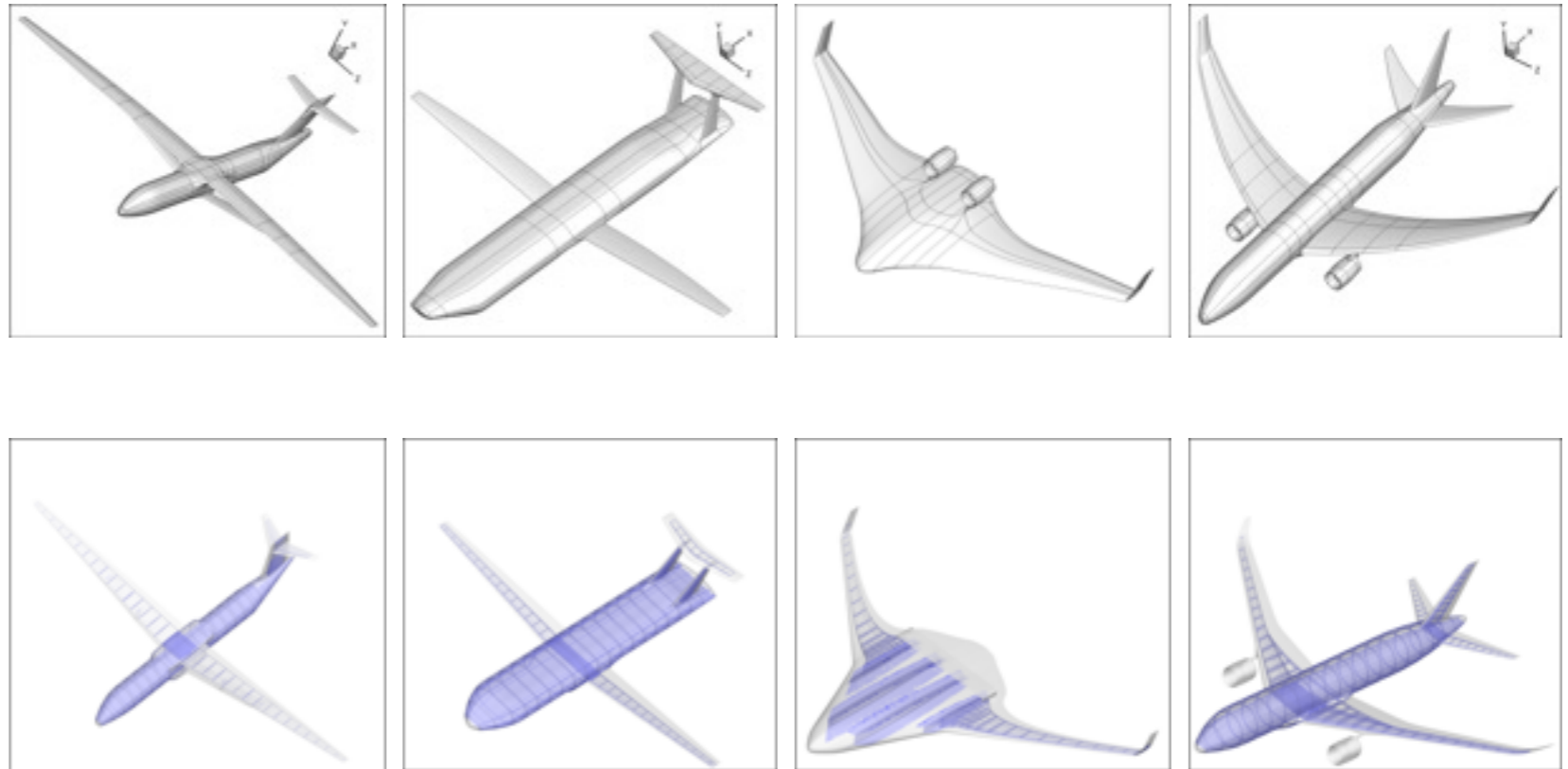


## Subproject 3

# Aerostructural modeling and optimization of the truss-braced wing aircraft



**To model the TBW, we use GeoMACH,  
which was developed in an earlier NASA effort**



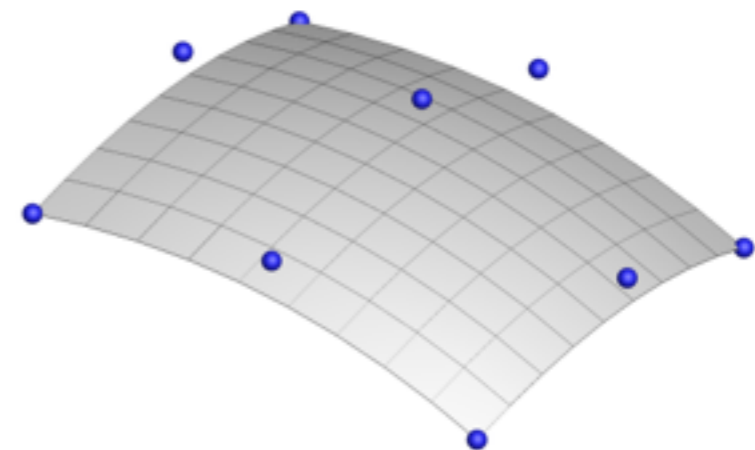
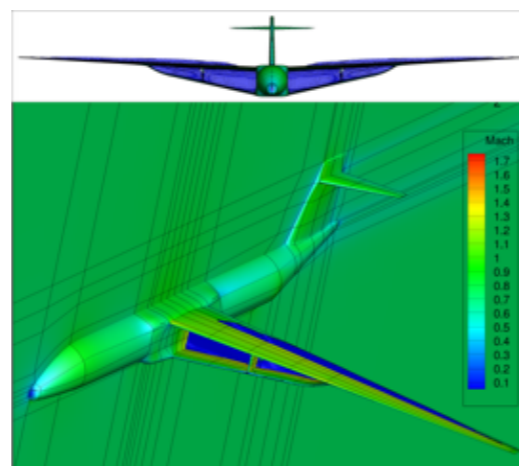
GeoMACH models aircraft geometries and structures  
using a differentiable parametrization

# To investigate the aerodynamics near the strut, we performed Euler-based shape optimization

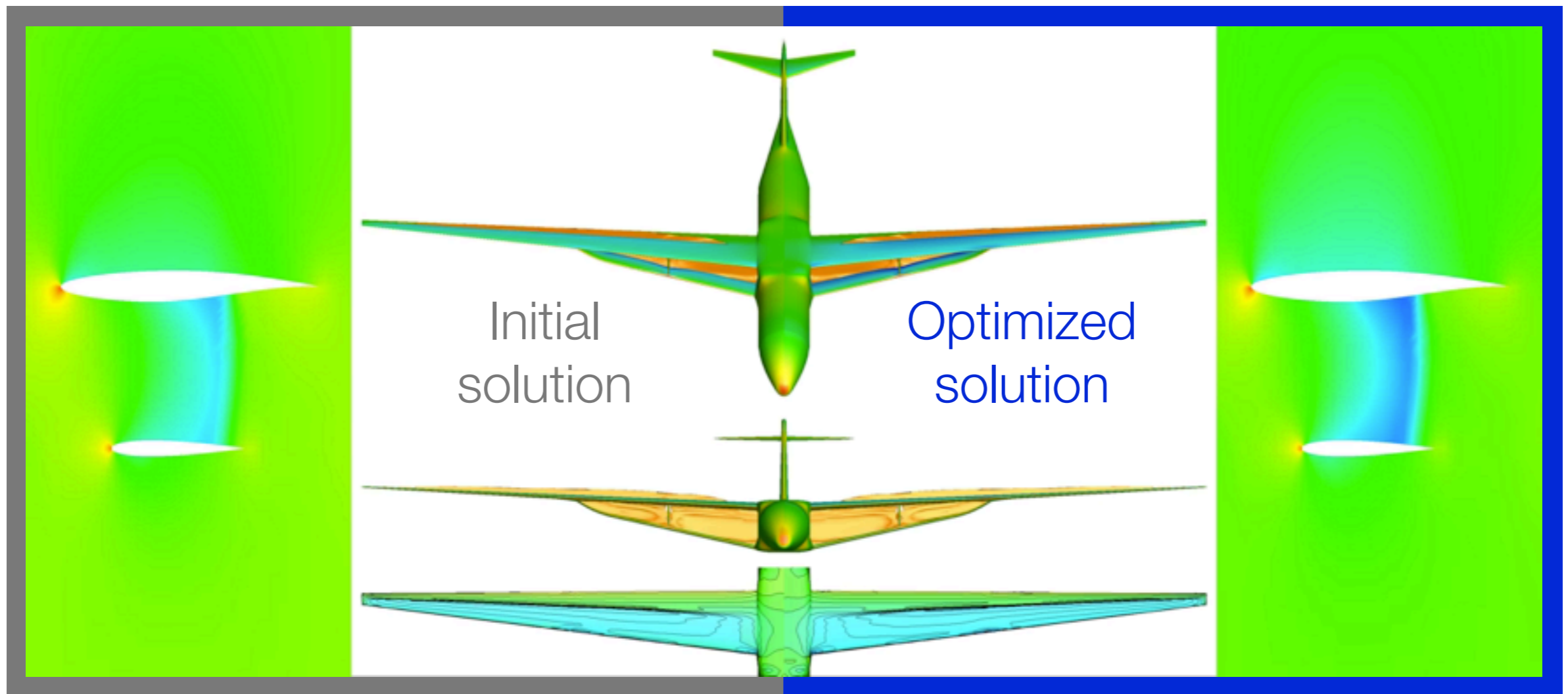
minimize drag coefficient

with respect to	angle of attack	1
	fuselage shape variables	25
	wing shape variables	200
	strut shape variables	128
	v. strut shape variables	50
	tail shape variables	<u>128</u>
		532

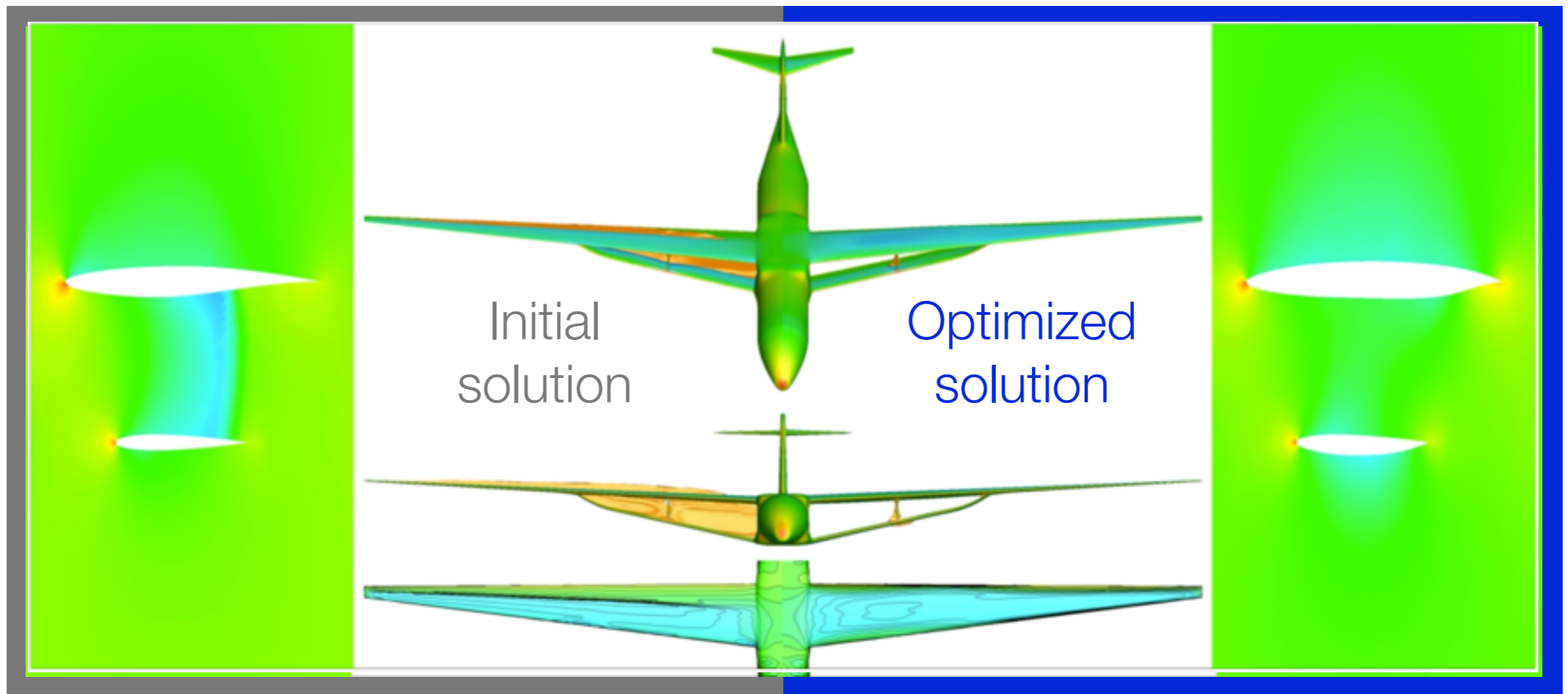
subject to lift coefficient constraint (0.5)



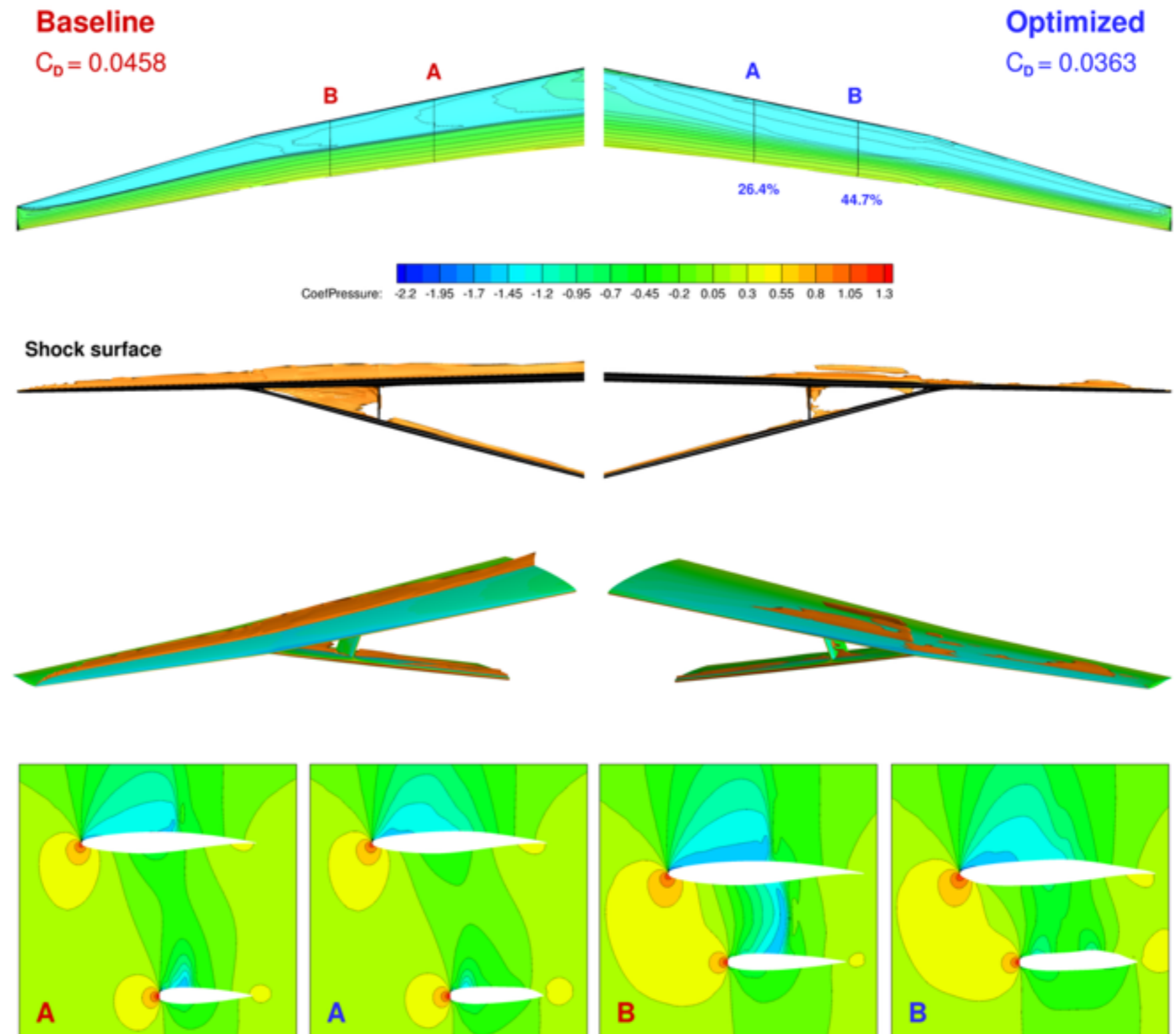
**Shape optimization eliminates the shock  
and reduces the drag by 58%**



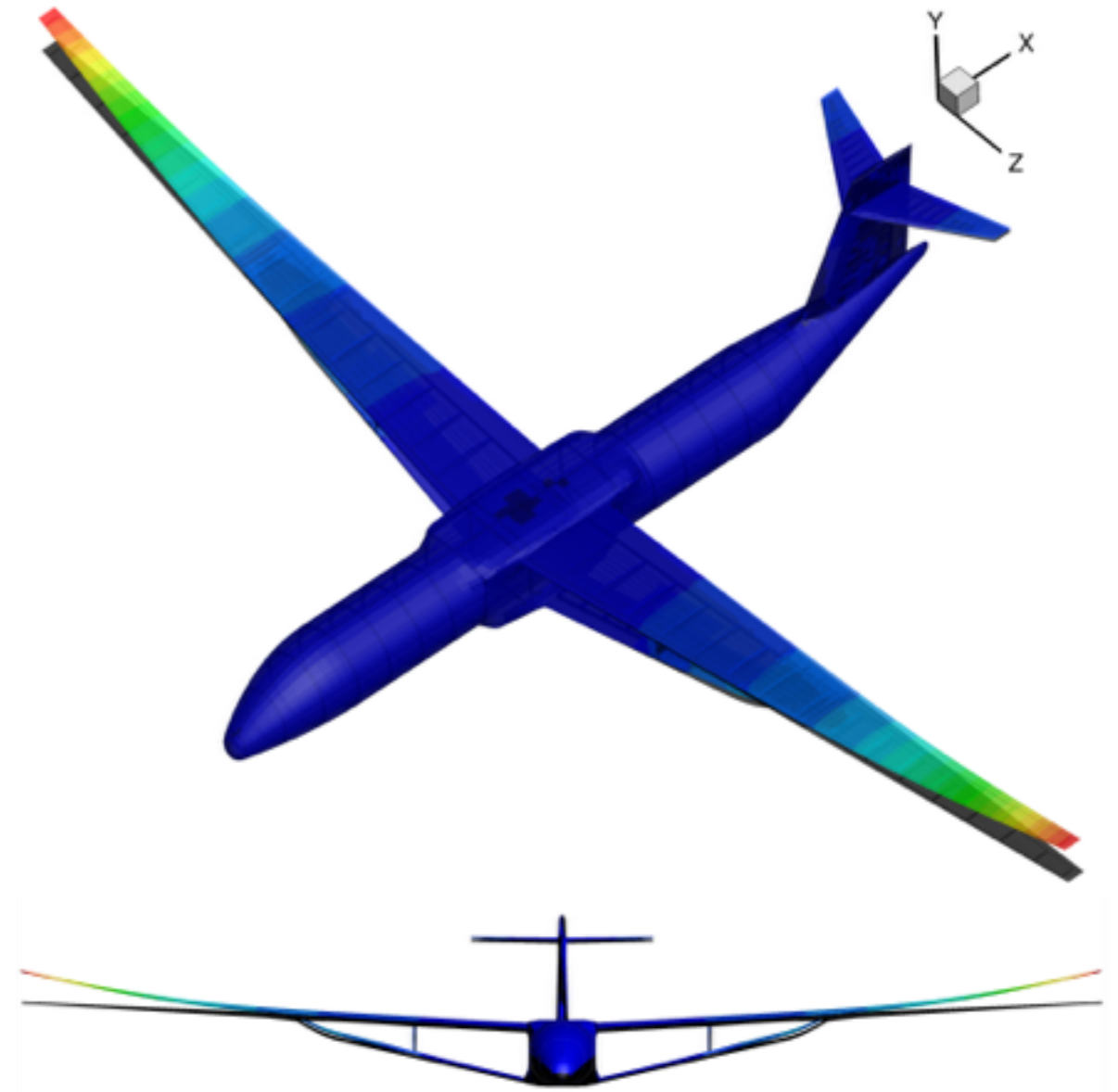
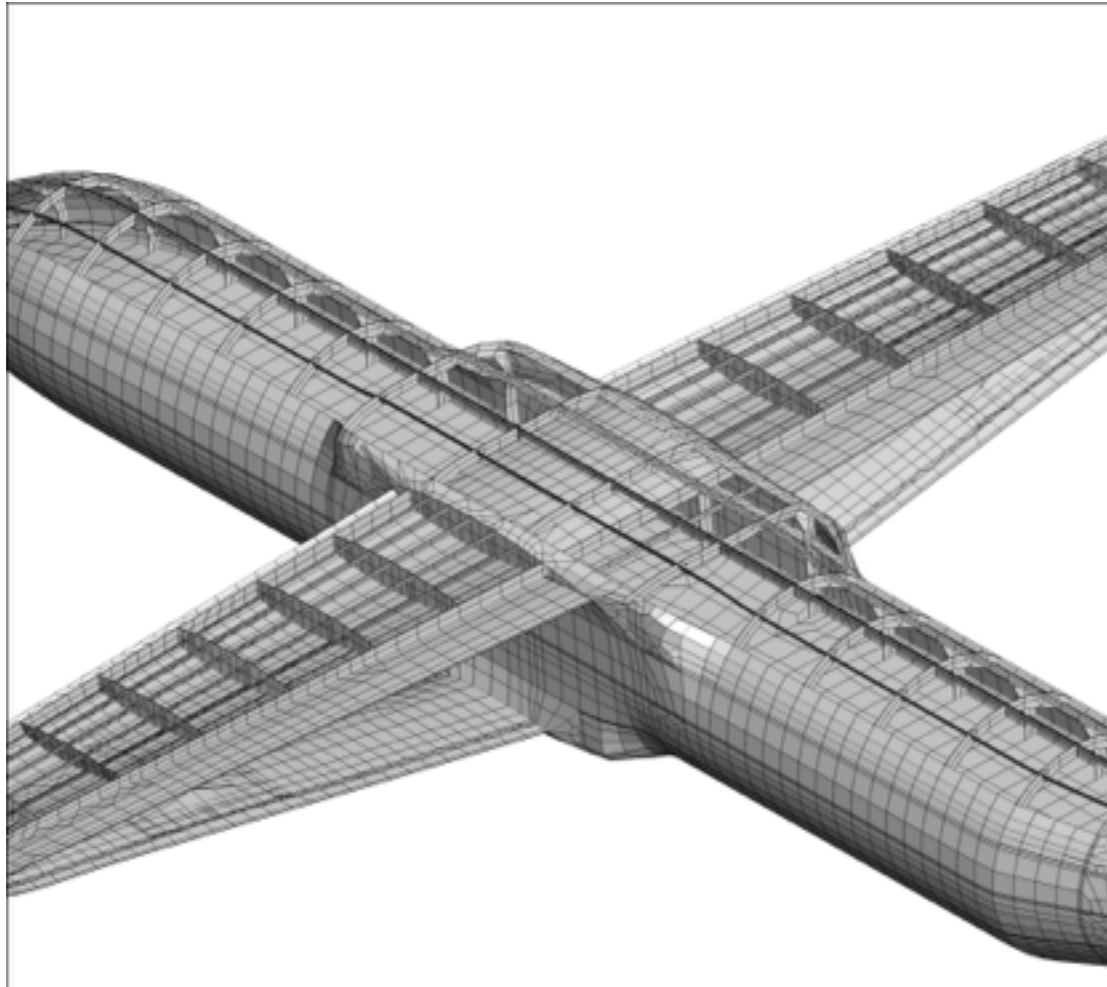
# Shape optimization eliminates the shock and reduces the drag by 58%



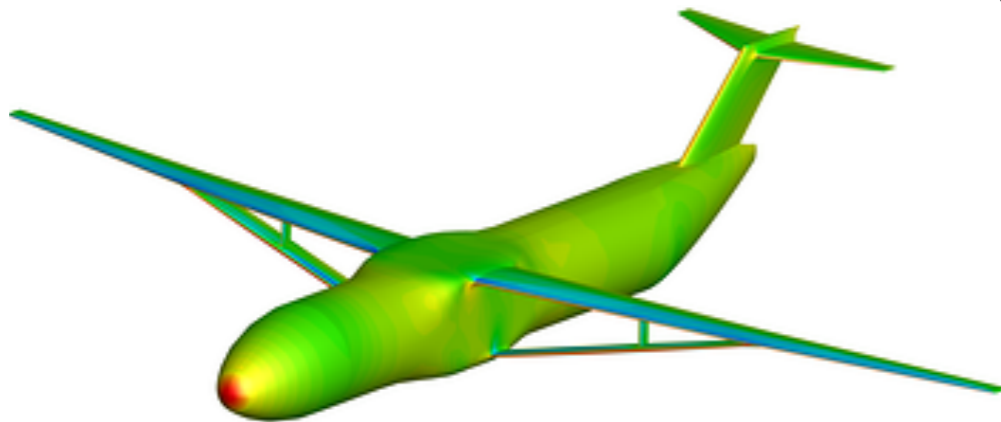
# We obtained similar results with the RANS equations



**We also developed a structural model  
for the truss-braced wing using GeoMACH**



# Summary for Subproject 3

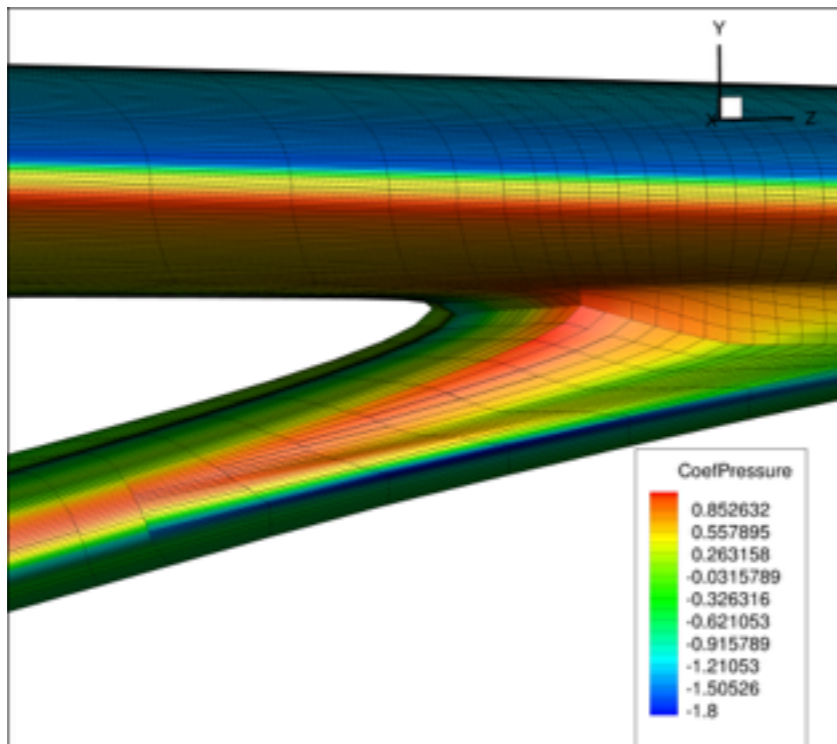


## Year 1 achievements:

- ▶ Developed geometries for the wing & struts and for the full TBW configuration
- ▶ Performed aerodynamic shape optimization to eliminate the shock
- ▶ Began development of a structural model for the TBW

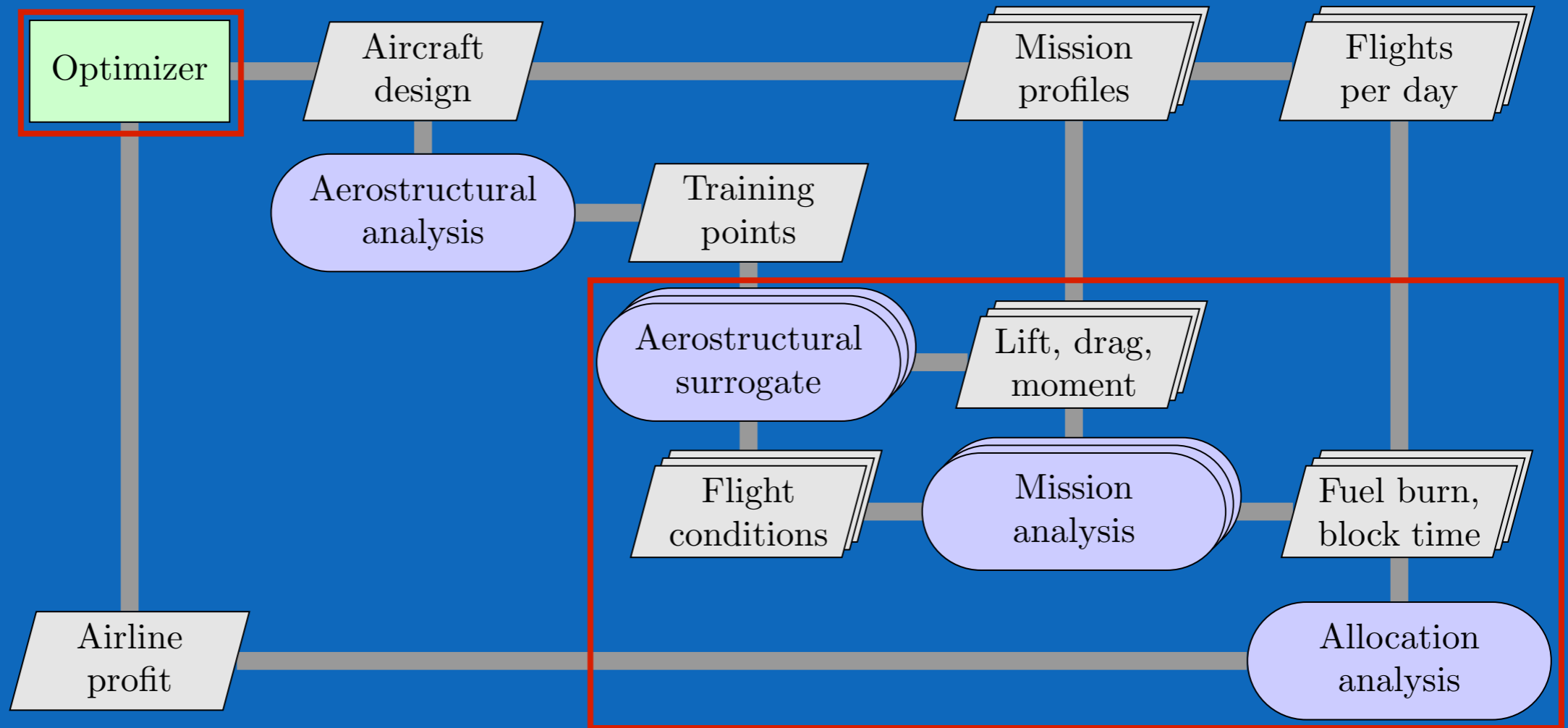
## Next steps:

- ▶ Perform detailed shape optimization
- ▶ Perform aerostructural optimization
- ▶ Develop an aerostructural surrogate model

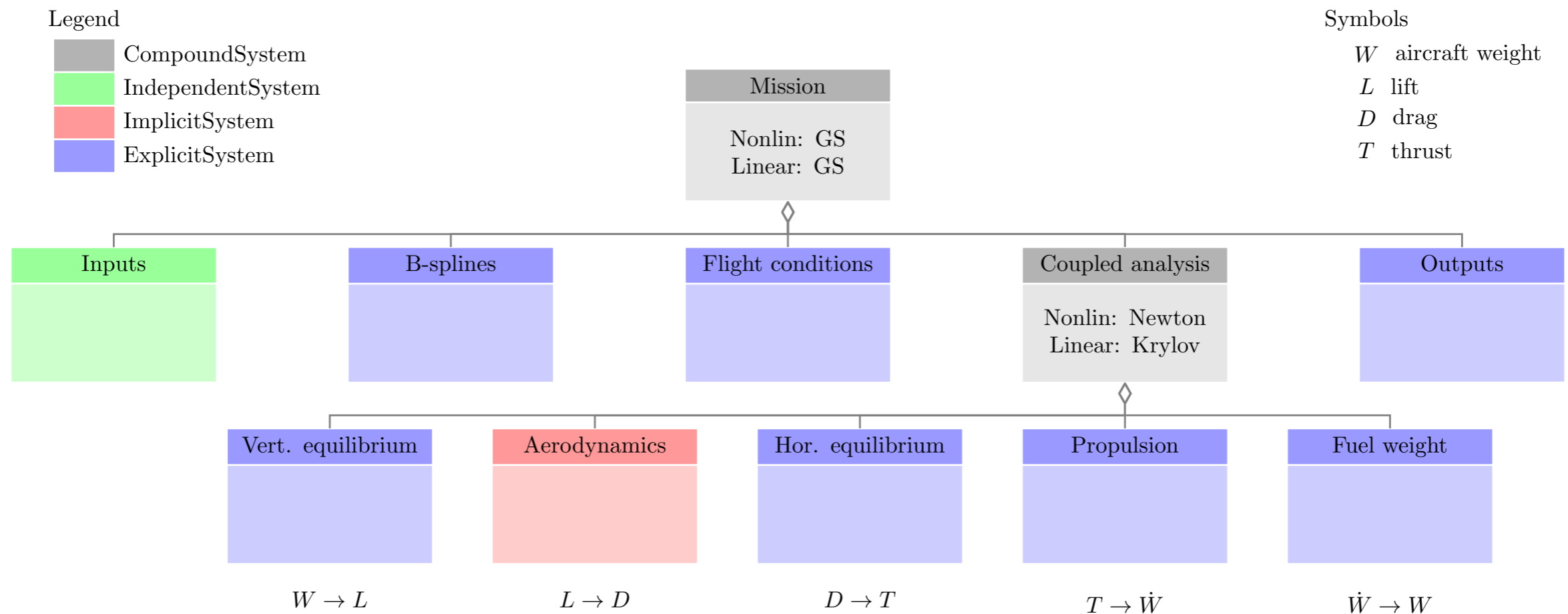


## Subproject 4

# Mission and allocation modeling and optimization



# We developed a unique mission analysis tool within the parallel framework



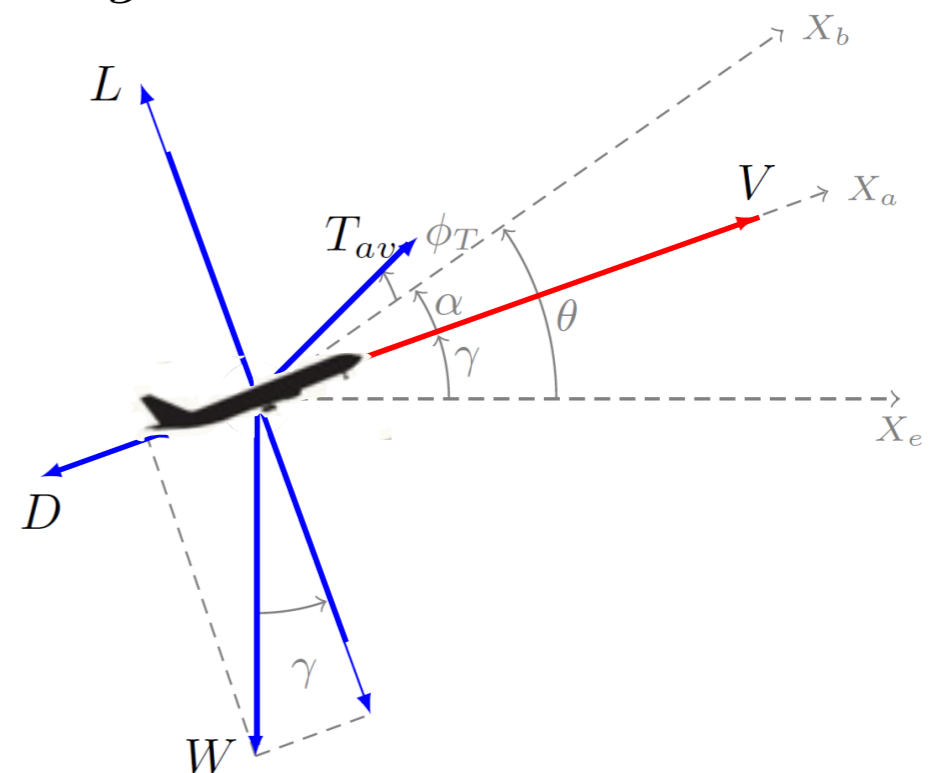
The framework automatically computes derivatives using the adjoint method

# The mission analysis solves the flight equilibrium equations

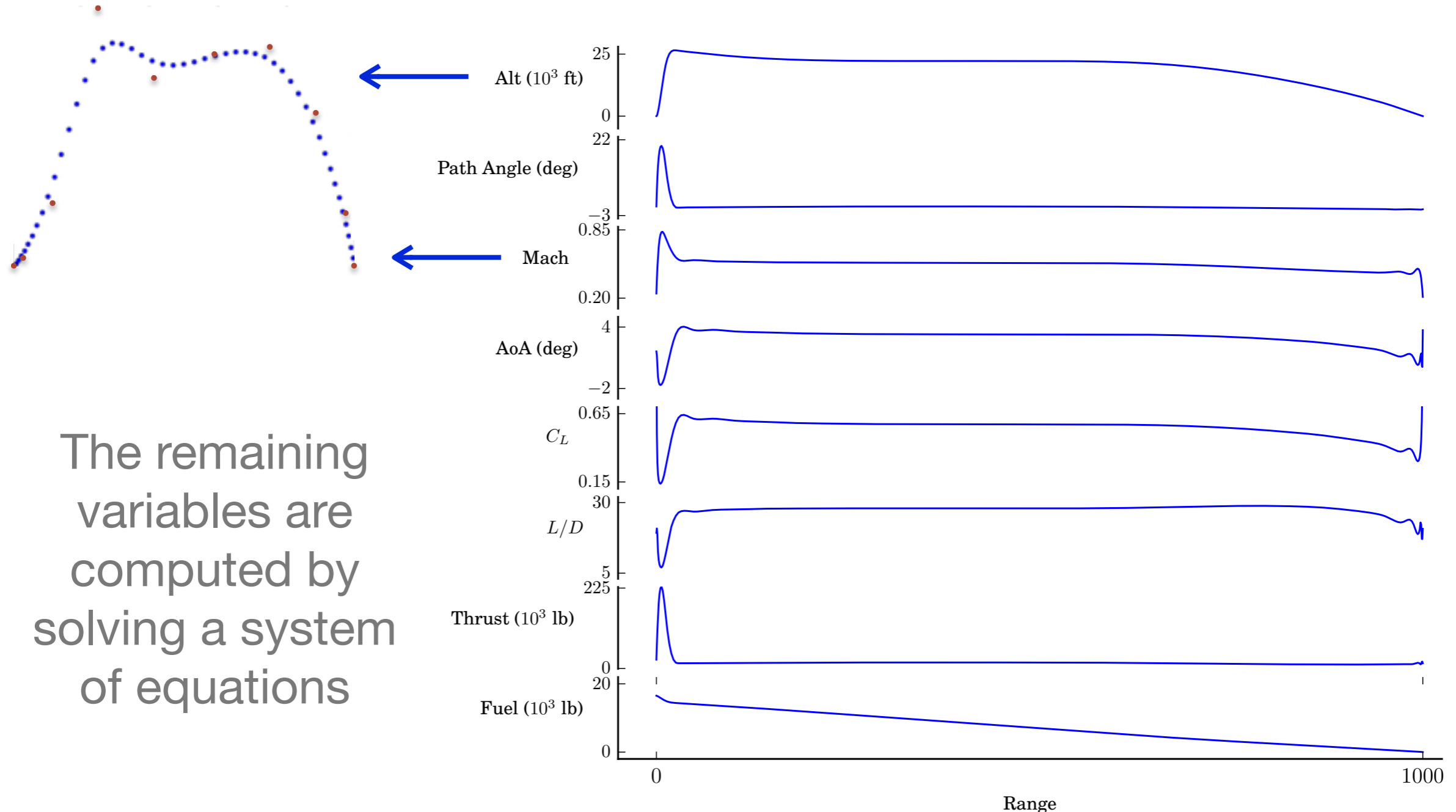
$$L + W \cos \gamma - T \sin \alpha + \frac{W}{g} v^2 \cos \gamma \frac{d\gamma}{dx} = 0$$

$$T \cos \alpha + D + W \sin \gamma + \frac{W}{g} v \cos \gamma \frac{dv}{dx} = 0$$

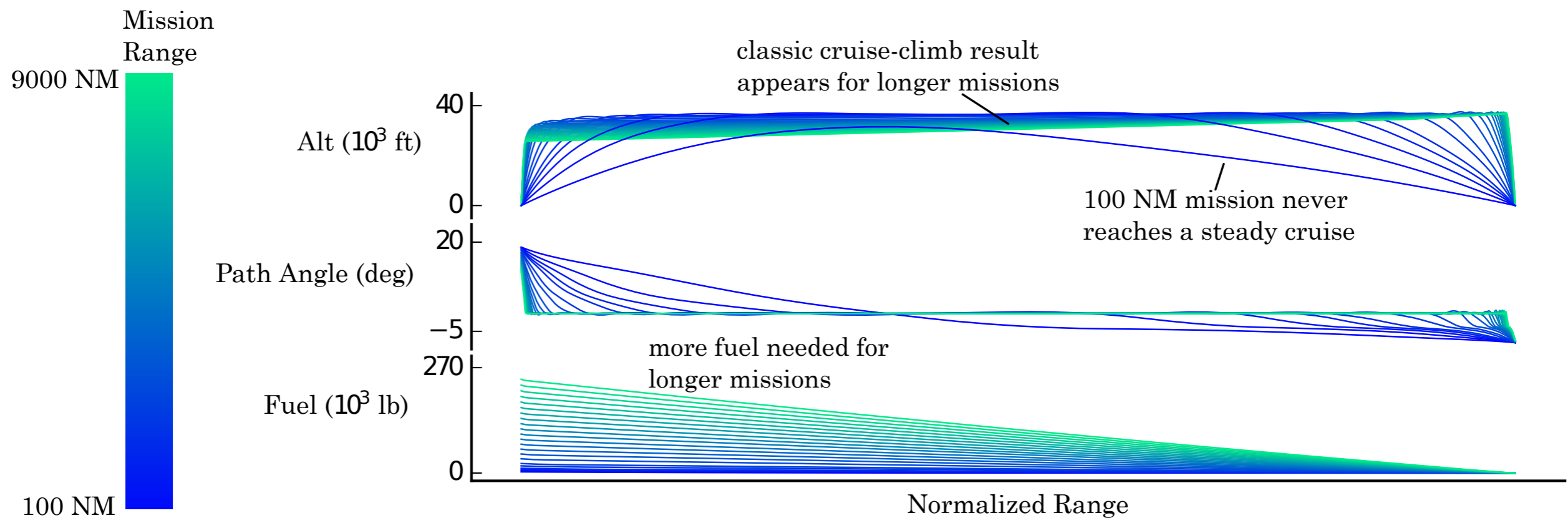
$$\frac{dW_f}{dx} = \frac{\text{SFC} \frac{1}{2} \rho v^2 S C_T}{v \cos \gamma}$$



# The altitude and Mach profiles can be optimized using a B-spline parametrization



# Multiple trajectories can be optimized quickly



# The allocation problem seeks to maximize profit

maximize profit

with respect to flights/day for each route and a/c  
pax/flight for each route and a/c  
altitude profiles for each route and a/c

subject to mission profile constraints  
route demand constraints  
aircraft availability constraints

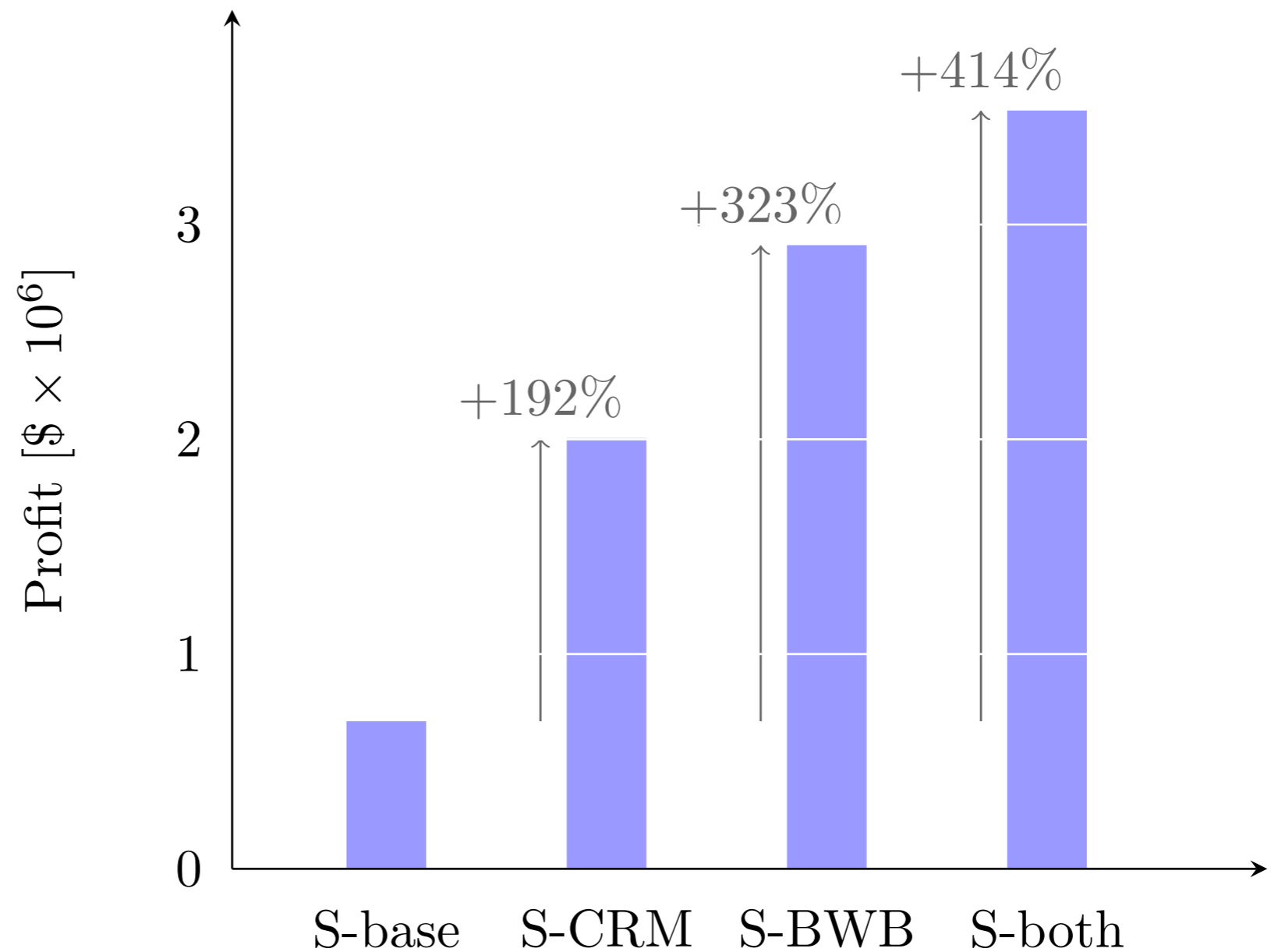


# We tested allocation-mission optimization on a 3-route test problem



Aircraft	Boeing 737-800	Boeing 777-200ER	Boeing 747-400	Boeing 787-8	CRM: advanced conventional	BWB: blended wing body
Category	Existing	Existing	Existing	Existing	New	New
Capacity	122	207	294	200	300	400
Scenario						
S-base	20	24	24	8		
S-CRM	20	24	24		8	
S-BWB	20	24	24			8
S-both	20	20	20		8	8

# Allocation-mission optimization yielded large profit increases with next-generation aircraft

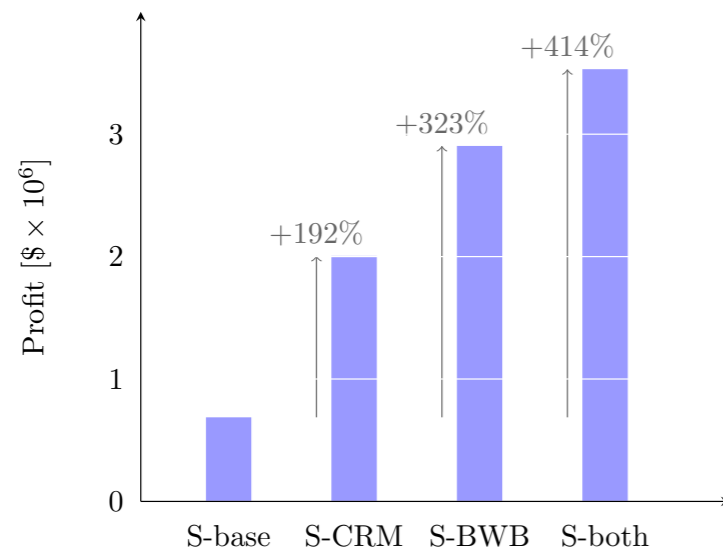
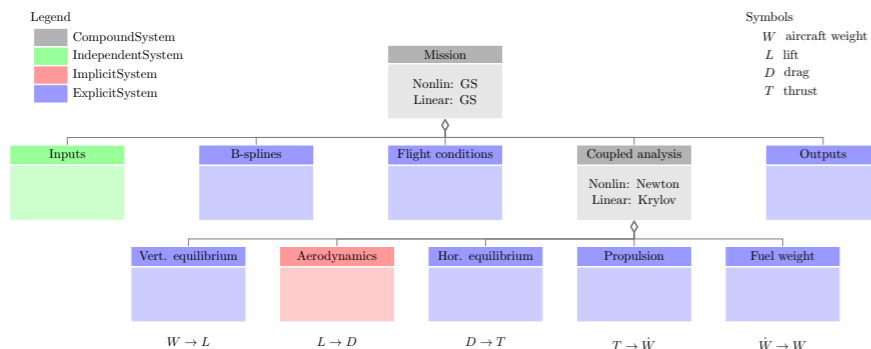


[Hwang, Roy, Kao, Martins, and Crossley, AIAA 2015-0900]

# Summary for Subproject 4

## Year 1 achievements:

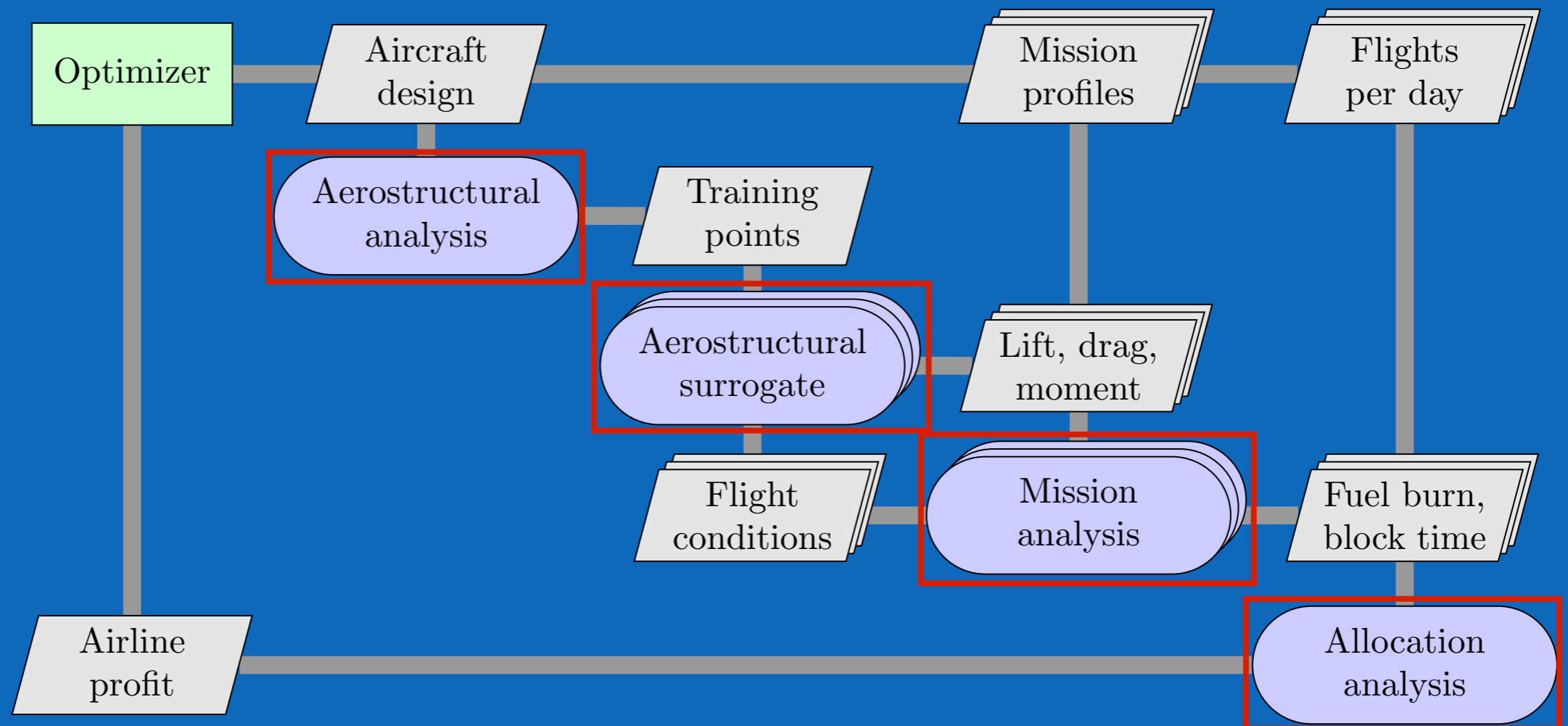
- ▶ Developed an efficient mission analysis & optimization tool with analytic derivatives
- ▶ Implemented allocation-mission optimization
- ▶ Developed a method for solving the mixed-integer nonlinear optimization problem



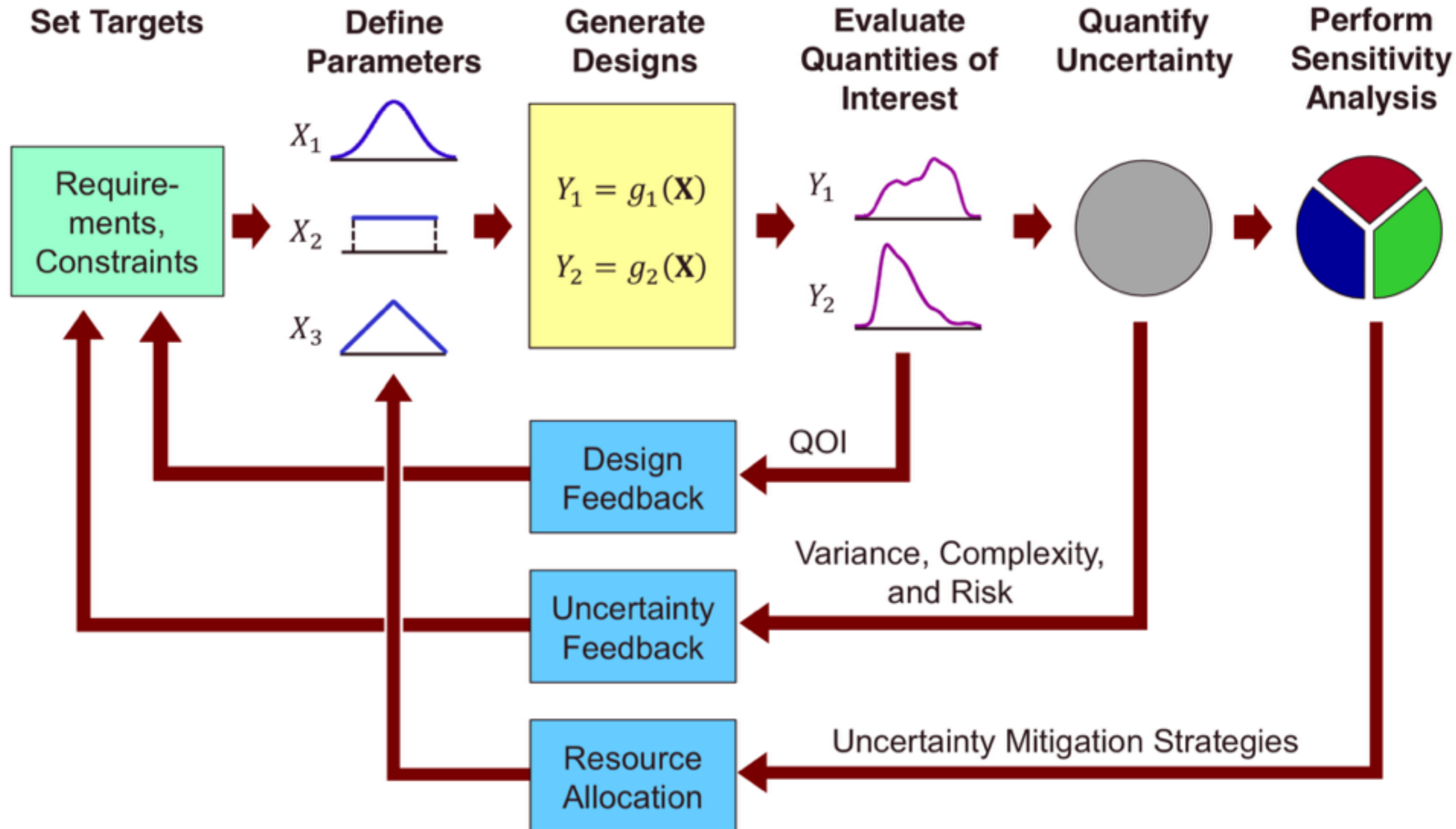
## Next steps:

- ▶ Parallelize the allocation-mission optimization
- ▶ Solve the problem with larger networks
- ▶ Perform allocation-mission-design optimization

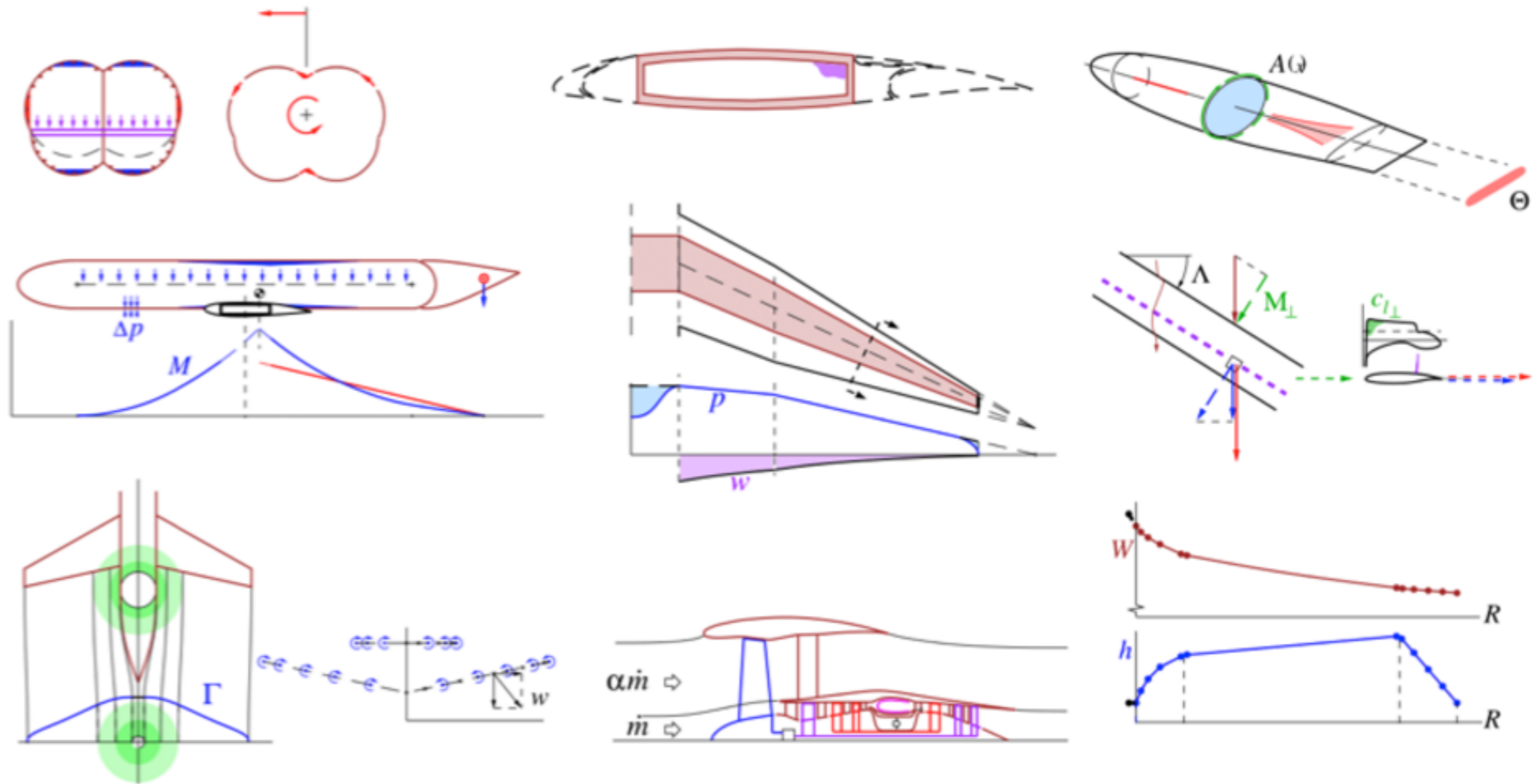
# Subproject 5: Uncertainty quantification for multifidelity design



# We cast the multidisciplinary system design as an estimation problem

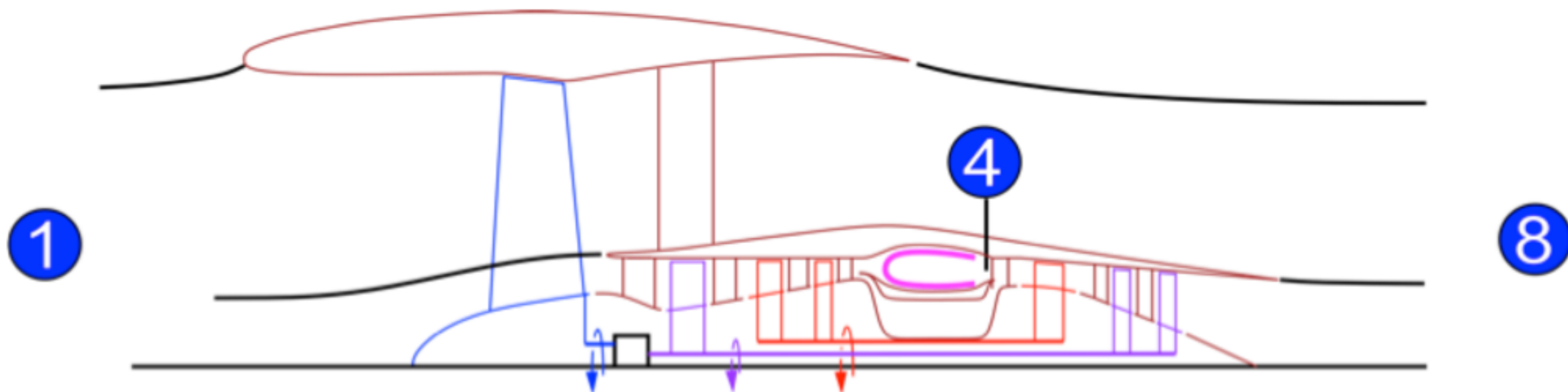


# To demonstrate the approach, we solve an aircraft sizing problem using TASOPT



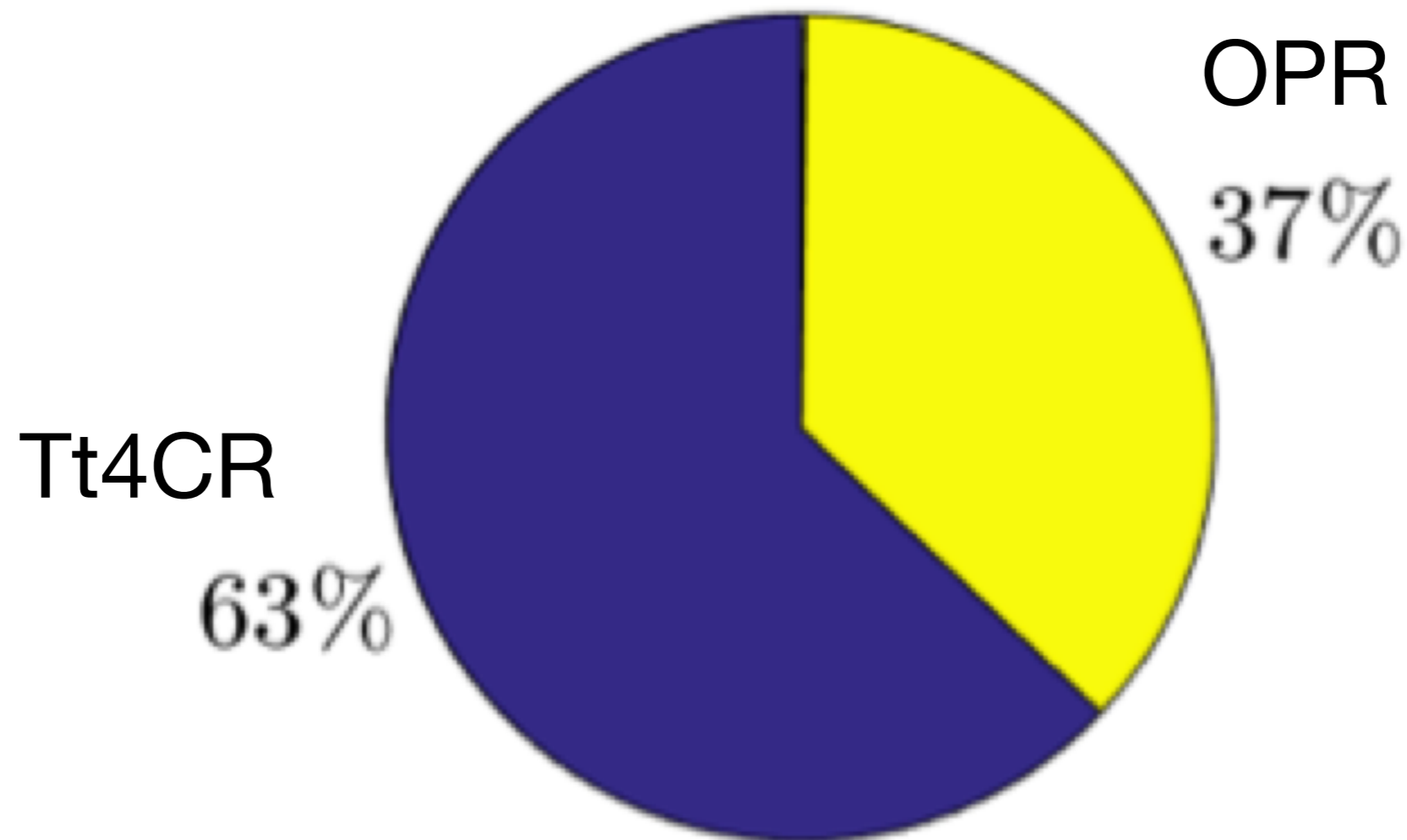
We focus on quantifying the sensitivities  
to the uncertainty of future engine performance

$T_{t4CR}$  total temperature at turbine inlet in cruise  
 $OPR$  overall pressure ratio



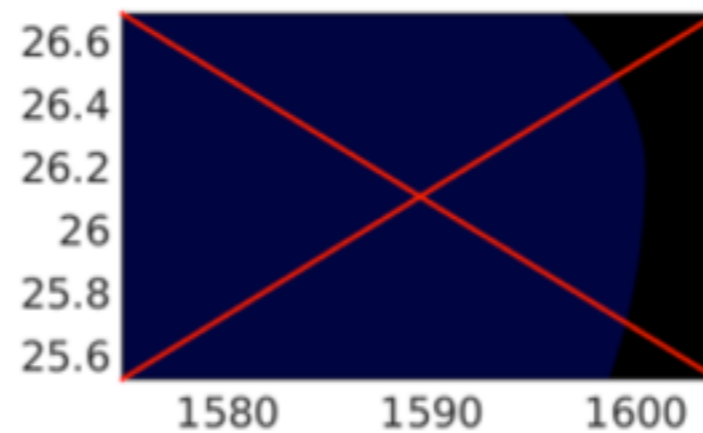
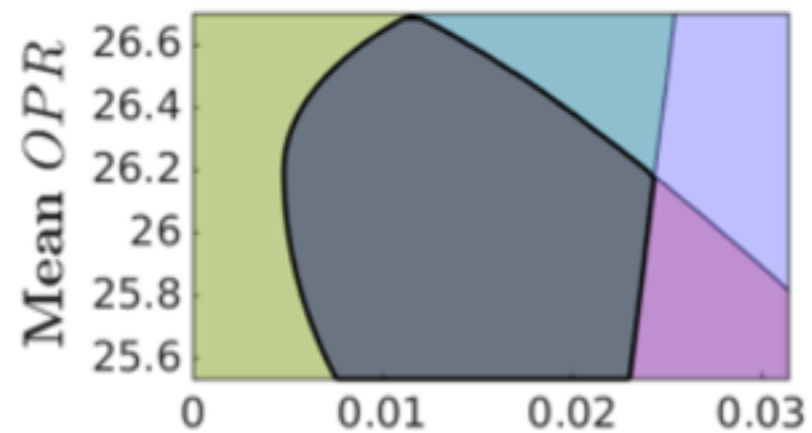
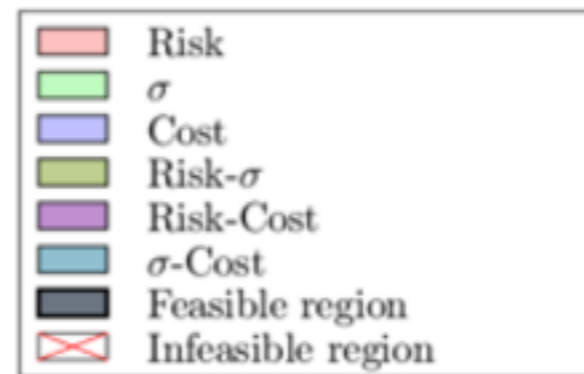
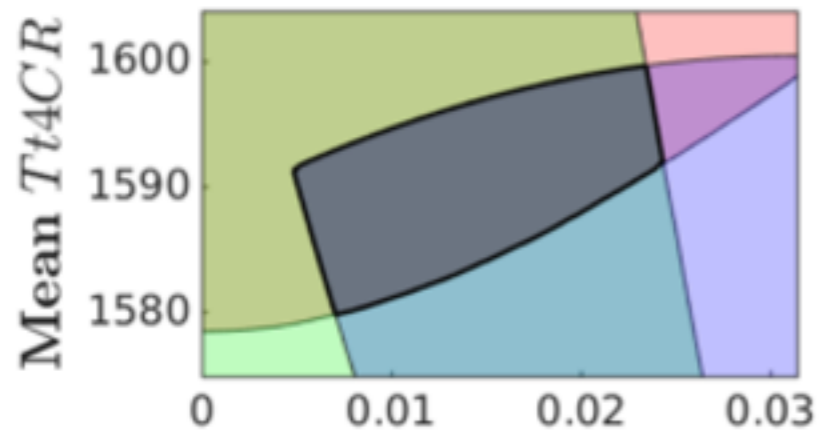
$PFEI$  fuel energy consumption  
per payload-range

# Our approach to global sensitivity analysis yields design insights

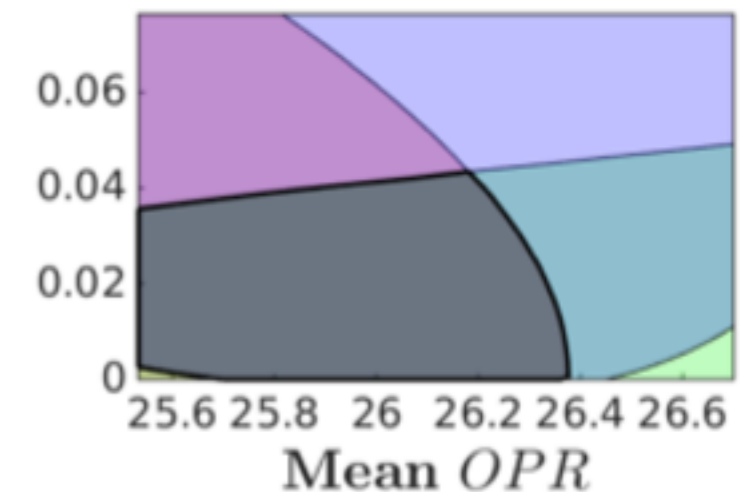
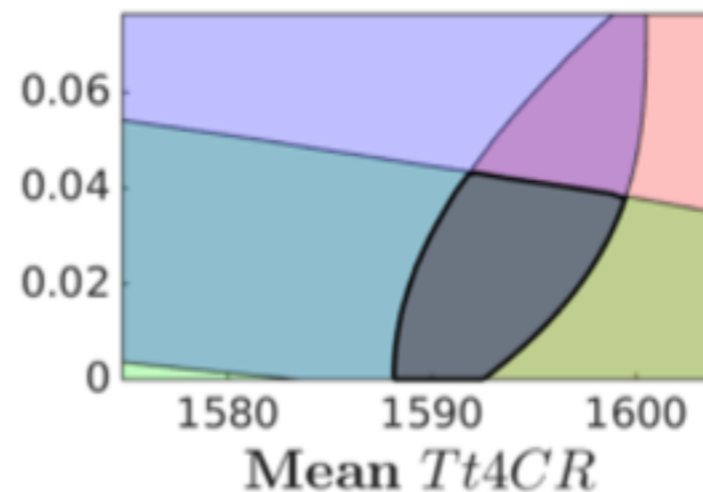
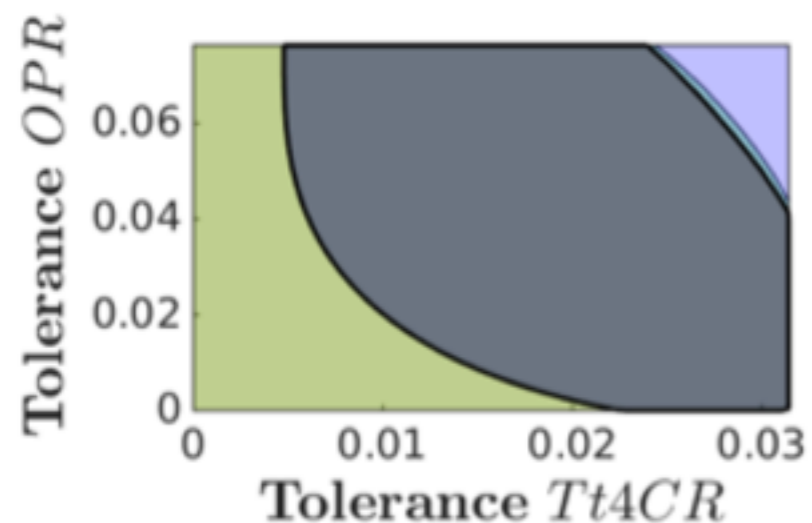


There are no interaction terms in this case

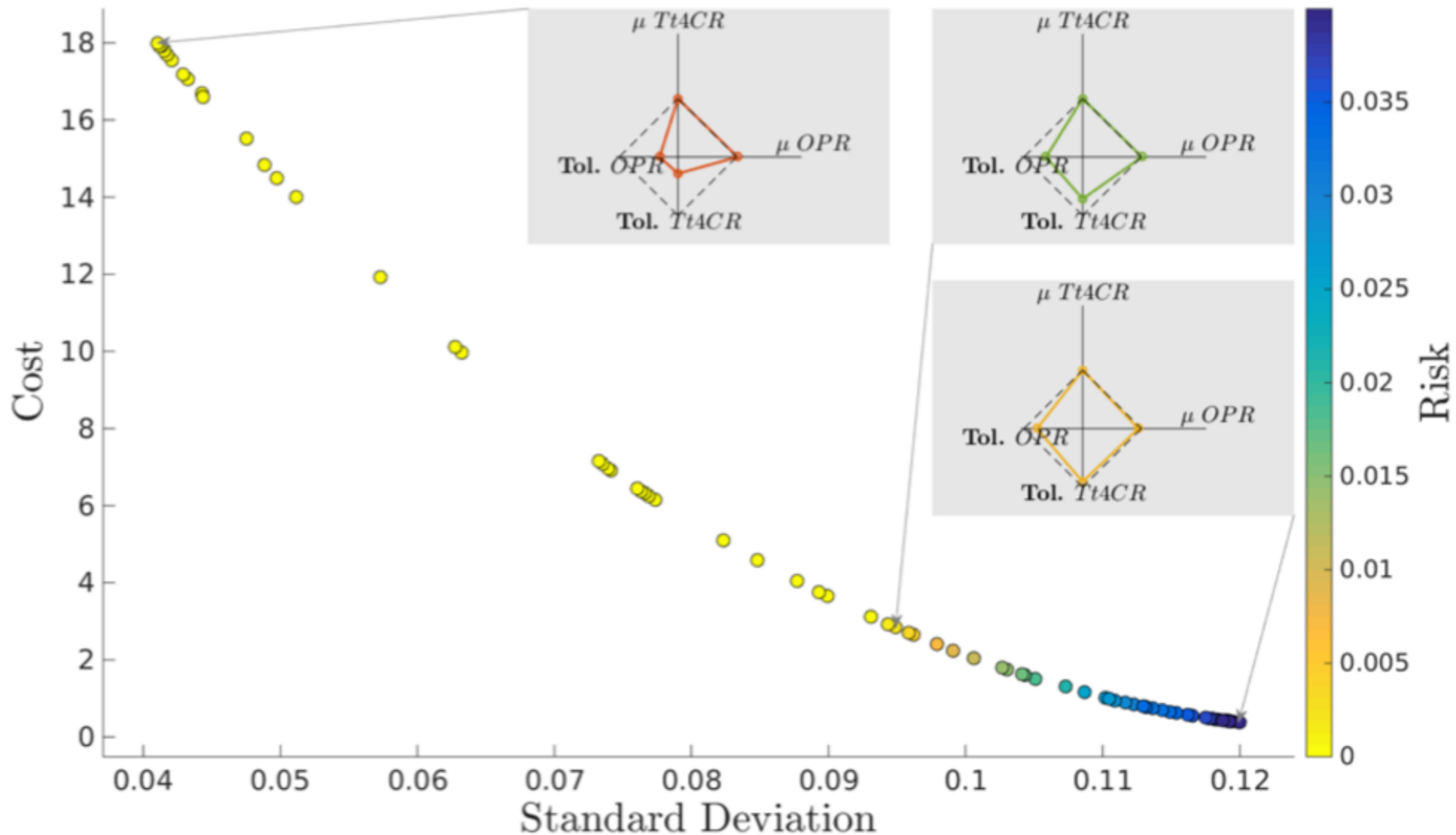
# The results also provide insight into how we can satisfy cost and uncertainty budgets



PFEI	
Risk	< 0.04
$\sigma$	< 0.12
Cost	< 18.00

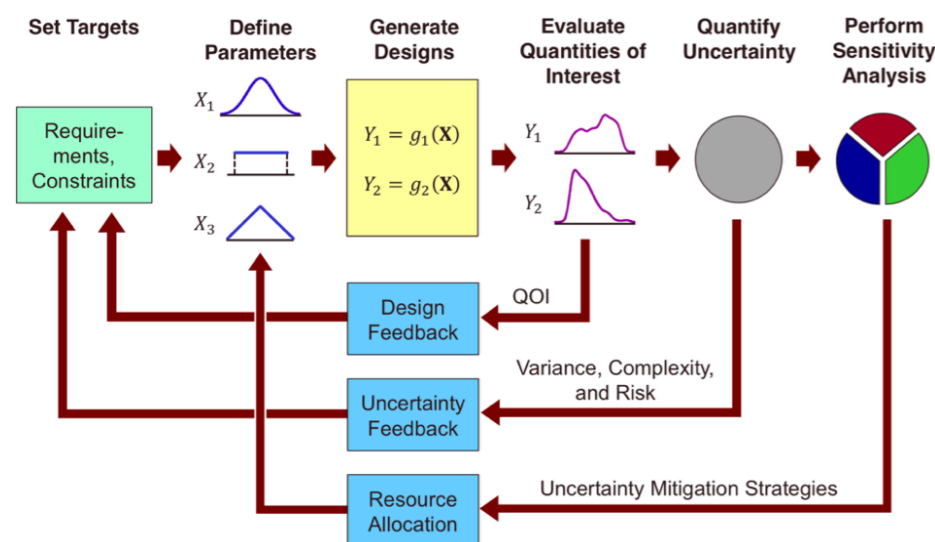


Using these tools, we can quantify the tradeoffs between cost, standard deviation, and risk



# Summary for Subproject 5

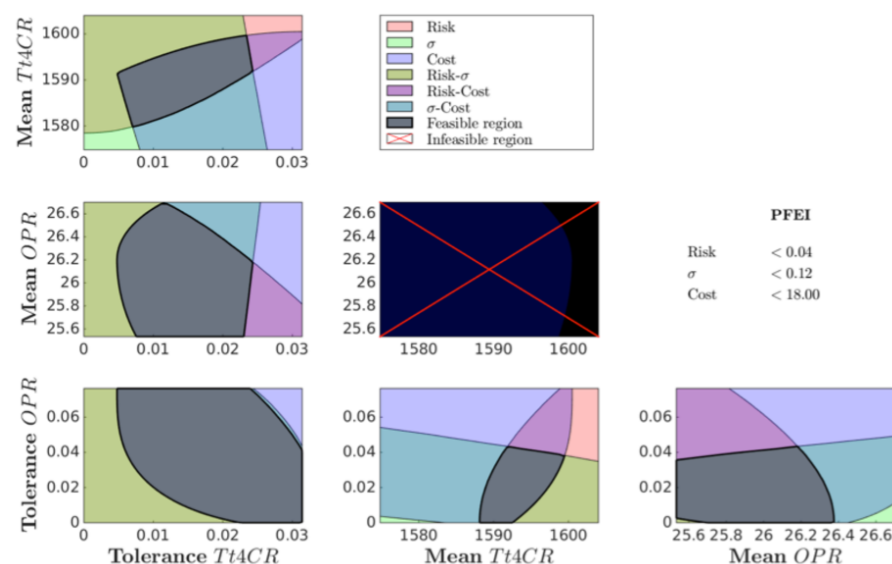
## Year 1 achievements:



- ▶ Developed UQ approach for managing risk in early stage aircraft design
- ▶ Demonstrated approach by quantifying effect of engine technology uncertainty on fuel burn

## Next steps:

- ▶ Extend UQ approach to consider nonlinear interactions
- ▶ Complete and demonstrate multi fidelity approach



# This project has yielded 7 publications so far

1. J. T. Hwang, S. Roy, J. Y. Kao, J. R. R. A. Martins, and W. A. Crossley. Simultaneous aircraft allocation and mission optimization using a modular adjoint approach. In Proceedings of the 56th AIAA/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference, Kissimmee, FL, Jan. 2015. AIAA 2015-0900.
2. J. Y. Kao, J. T. Hwang, J. R. R. A. Martins, J. S. Gray, and K. T. Moore. A modular adjoint approach to aircraft mission analysis and optimization. In Proceedings of the AIAA Science and Technology Forum and Exposition (SciTech), Kissimmee, FL, January 2015. AIAA 2015-0136.
3. J. T. Hwang, G. K. W. Kenway, and J. R. R. A. Martins. Geometry and structural modeling for high-fidelity aircraft conceptual design optimization. In Proceedings of the 15th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, Atlanta, GA, June 2014. AIAA 2014-2041.
4. J. Gray, T. Hearn, K. Moore, J. T. Hwang, J. R. R. A. Martins, and A. Ning. Automatic evaluation of multidisciplinary derivatives using a graph-based problem formulation in OpenMDAO. In Proceedings of the 15th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, Atlanta, GA, June 2014. doi:10.2514/6.2014-2042.
5. Hicken and Dener, A Flexible Iterative Solver for Nonconvex, Equality-Constrained Quadratic Subproblems, SIAM Journal on Scientific Computing (Submitted).
6. J. T. Hwang and J. R. R. A. Martins. A parallel hierarchical algorithmic framework for large-scale simulation and optimization. SIAM Journal of Scientific Computing, 2015. (To be submitted).
7. A. Dener, J. E. Hicken, G. K. W. Kenway, Z. Lyu, and J. R. R. A. Martins. Aerostructural design optimization of an adaptive morphing trailing edge wing. In Proceedings of the AIAA Science and Technology Forum and Exposition (SciTech), Kissimmee, FL, January 2015. AIAA 2015-1129.

# Summary of novel contributions so far

1. A new modular, scalable, and general numerical optimization algorithm that handles parallel problems
2. A new parallel, scalable algorithmic framework for multidisciplinary analysis and gradient computation (now implemented in OpenMDAO)
3. A matrix-free CFD adjoint
4. An adjoint-based mission analysis and trajectory optimization code
5. A method for simultaneously optimizing aircraft trajectory and allocation
6. A framework for performing aircraft design optimization under uncertainty

# Thank you!

